Government Debt and the Returns to Innovation

M. Croce T. Nguyen S. Raymond L. Schmid*

Abstract

Elevated levels of government debt raise concerns about their effects on long-term growth prospects. Using the cross section of US stock returns, we show that (i) high-R&D firms are more exposed to government debt and pay higher expected returns than low-R&D firms; and (ii) higher levels of the debt-to-GDP ratio predict higher risk premia for high-R&D firms. Furthermore, rises in the cost of capital for innovation-intensive firms predict declines in subsequent productivity and economic growth. We propose a production-based asset pricing model with endogenous innovation and fiscal policy shocks that can rationalize key aspects of the empirical evidence.

JEL classification: E22; E62; H30; O33; O41.
Keywords: Government Debt, Fiscal Uncertainty, Cross Section of Stock Returns, Predictability, R&D, Growth
This draft: July 4, 2017.

*Croce is affiliated with the University of North Carolina at Chapel Hill, Kenan-Flagler Business School. Nguyen is affiliated with the Ohio State University, Fisher College of Business. Raymond is a PhD student in the Economics Department of the University of North Carolina at Chapel Hill. Schmid is affiliated with Duke University, Fuqua School of Business, and CEPR. We are grateful for feedback from Justin Birru, Nina Boyarchenko, Sergey Chernenko, Diego Comin, Joao Gomes, Kewei Hou, Timothy Johnson, Dana Kiku, Lars-Alexander Kuehn, Xiaoji Lin, Indrajit Mitra, Joshua Pollet, and Amir Yaron. We thank the seminar participants at the Wharton School, the Finance Department at the Erasmus University, the UIUC College of Business, the Kenan-Flagler Business School (UNC), the Fuqua School of Business (Duke University), the Fisher College of Business (OSU), Olin Business School (Washington University), Scheller College of Business (Georgia Institute of Technology), Universita' Bocconi, Tsingua University, the SED Conference, SFS Finance Cavalcade Conference, the Econometric Society Meetings, the RCEF Conference, the CEPR Summer Meetings, the WFA meetings, and The University of St. Gallen Conference on Growth.

1 Introduction

Fiscal stabilization policies implemented in response to the recent great recession have led to a surge in government debt across the globe. A common concern is that the budget consolidation processes required by this debt will come at the cost of dimmer long-run growth prospects. Such concerns are based on expectations of either higher future tax pressure or raises in average inflation through attempts to inflate debt away, as well as on the political uncertainty surrounding the restoration of a balanced budget. While these adverse effects of debt and fiscal policy on economic growth are well grounded in economic theory, the empirical evidence in their support in cross-country tests has been weak or ambiguous, perhaps because of short samples and small cross sections.

In this paper, we propose a different perspective based on a large cross section of US firms. We highlight a novel and distinct mechanism shaping the link between public debt and future growth, namely a *risk* channel. More specifically, we identify innovations to government indebtedness as a risk factor priced in both the cross section and the time series of stock returns. By affecting their cost of capital, movements in government debt impact firms' investment and, critically, innovation decisions. Empirically, we implement powerful tests of this link on the entire cross-section of US stock returns, and interpret and quantify them through the lens of a production-based asset pricing model with endogenous innovation and growth.

Our analysis starts from the empirical observation that the government debt–to–GDP ratio, $DGDP$ for short, significantly predicts higher future aggregate stock returns at longer horizons, even after we control for standard predictors such as the price-dividend ratio and market volatility. In other words, investors perceive episodes of high government debt as bad times. This finding suggests that news to government debt is a risk factor priced in the cross section of stock returns, as investors are hesitant to incur losses on stocks in times of rising debt. Indeed, we find that about one third of the well documented premium of R&D-intensive stocks over less innovative stocks—hereafter, the return on what we call the

HML-R&D portfolio—can be attributed to exposure to fiscal variables. In the time series, we show that this premium rises when government debt increases. In other words, our asset pricing tests suggest that rises in government debt increase the cost of capital, especially for innovative firms.

Critically, we document that movements in the cost of capital of innovative firms in response to surges in government debt predict slowdowns in innovative activity and declines in growth prospects at longer horizons. For example, an increase in the expected excess return of the *HML-R&D* portfolio forecasts a significant decline in output and productivity growth over a horizon of 20 quarters. This is because rises in $DGDP$ are accompanied by subsequent declines in corporate investment and R&D. At the same time, a reallocation towards investment in physical capital occurs, as innovation is depressed relatively more. Our mechanism thus complements the work of Belo, Gala, and Li (2013) and Belo and Yu (2013), who examine the effects of government investment and spending on asset prices.

To interpret our findings and provide guidance on further empirical tests, we develop a quantitative model of a stochastic production economy in which endogenous innovation drives growth prospects and the Ricardian equivalence does not hold. Specifically, we focus on an economy with two capital stocks, one of which is comprised of intangible innovations (for a complementary approach with more firm heterogeneity, see Gomes, Michaelides, and Polkovnichenko (2010, 2012)). The government finances expenditures by issuing debt and levying distortionary taxes on corporate profits according to fiscal rules that determine the extent of fiscal stabilization through tax smoothing (i.e., the persistence and the volatility of the tax rate). Movements in government debt drive the dynamics of tax rates, which affect corporate investment and innovation and thus equilibrium growth.

We find that the model quantitatively rationalizes our empirical evidence on return predictability well when we allow for shocks to productivity, government expenditures, and government financing. Financing shocks alter the government's stance regarding deficit spending. In our general equilibrium setting, all of these three shocks are reflected in the

stochastic discount factor and hence give rise to a three-factor asset pricing model. More specifically, we show that our general equilibrium model predicts nearly constant negative market prices of debt policy and government expenditure risks, and exposures of returns to fundamental shocks that are nearly affine in $DGDP$. As a result, the reduced form of our equilibrium model is a three-factor model with conditional betas that can be expressed as a linear function of $DGDP$. In our setting, a rising $DGDP$ level elevates the exposure of returns to the underlying risks and forces firms to cope with a higher cost of capital.

Our model also predicts that excess returns on *HML-R&D* are forecastable by $DGDP$ because the sensitivity of the cost of capital of innovative firms with respect to $DGDP$ is higher than that of low R&D-intensity firms. The mechanism behind this result can be explained as follows. As $DGDP$ increases, uncertainty about future tax rates rises endogenously and trickles down to all quantities in general equilibrium. Since the value of innovative firms is crucially driven by the present value of volatile monopolistic rents, R&D firms are more exposed to spikes in cash-flow uncertainty than non-R&D firms.

From the perspective of the representative household, such elevated exposure triggers a reallocation of investment towards tangible capital. With adjustment costs, the market value of low R&D-intensity firms falls less, so that they emerge as a hedge through this reallocation. This channel is stronger when the economy has higher values of $DGDP$.

As a result, less innovative firms are unconditionally less risky than R&D-intensive firms (e.g., our model-impled *HML-R&D* is positive as in the data) and relatively safer in high debt episodes (e.g., the model-implied *HML-R&D* grows with $DGDP$). Within the context of the model, this premium predominantly reflects elevated exposure to debt policy shocks. We view these shocks as arising from the budget negotiation process or from shifts in the political composition of the administration. Our model thus highlights the role of political risk in the determination of risk premia, in the spirit of Kelly, Pastor, and Veronesi (2015) and Pastor and Veronesi (2012, 2013).

We provide further evidence supporting our cost of capital mechanism by running stan-

dard cross-sectional asset pricing tests based on the conditional three-factor model implied by our production economy. This cross-sectional estimation is based on both R&D-sorted test assets as well as the twenty-five Fama-French size and book-to-market double-sorted portfolios. Our estimation results confirm significantly negative risk prices for fiscal risks, implying that sudden rises in $DGDP$ are indeed bad states for investors.

Moreover, in line with our model predictions, the expected excess return on *HML-R&D* is increasing in $DGDP$ so that high-R&D firms are more exposed to government debt and pay higher expected returns than low-R&D firms. Notably, these results hold even after controlling for standard financial risk factors, confirming a distinct role for fiscal factors both in the cross-section of innovation-sorted returns and for aggregate investment and growth.

Related Literature. Our paper contributes to several strands of literature. First, our study highlights the role of political risk in determining the cost of capital across innovation-sorted firms. In this regard, our analysis is related to the growing literature on policy uncertainty and asset markets (see, among others, Kelly, Pastor, and Veronesi (2015); Pastor and Veronesi (2012, 2013); Bloom (2009); Baker, Bloom, and Davis (2016); Manela and Moreira (2016); Gomes, Michaelides, and Polkovnichenko (2010, 2012); Gomes, Kotlikoff, and Viceira (2011); Glover, Gomes, and Yaron (2010); Sialm (2009); Sialm (2006); and Croce, Kung, Nguyen, and Schmid (2012)). Lustig, Sleet, and Yeltekin (2008) and Lustig, Berndt, and Yeltekin (2012) examine the nature of fiscal risks. In contrast to these studies, we examine the role of uncertainty about the fiscal stance in both the cross section and the time series of stock returns. Our results on the link between government borrowing and the cost of equity of innovation-intensive firms complement those by Graham, Leary, and Roberts (2014) in the corporate bonds market, and those by Demirci, Huang, and Sialm (2016) on corporate capital structures.

Our empirical asset pricing tests are in the spirit of recent and classic work emphasizing return predictability in the cross section and the time series. A nonexhaustive list of classic

papers on cross-sectional return predictability includes Fama and French (1992); Cochrane (1996); and Pastor and Stambaugh (2003). These papers establish a number of important tradable and macroeconomic factors priced in the cross section of stock returns. Recent work by Hou, Xue, and Zhang (2015a, b), Fama and French (2015), Belo, Bazdresch, and Lin (2011) and Lin (2012) adds novel factors related to corporate policies to that list, such as investment, R&D, hiring and profitability factors. We contribute to this literature by introducing a simple and economically meaningful predictor in both the cross section and the time series, namely our $DGDP$ factor.

Time-series predictability has been explored by Campbell and Shiller (1988), Cochrane (2008), Lettau and Ludvigson (2005), and Koijen, Lustig, and Van Nieuwerburgh (2010), among others. We document the relevance of $DGDP$ in this regard. In independent recent work, Bai (2016) and Liu (2016) empirically confirm that the government $DGDP$ ratio significantly predicts aggregate stock returns over longer horizons. In addition, we show that our $DGDP$ factor predicts not only aggregate stock returns, but also spreads between innovation-sorted portfolios in the time series and cross section. Furthermore, we explicitly link fiscal uncertainty, innovation, and growth, adding new insights to the findings of Easterly and Rebelo (1993); Mendoza, Milesi-Ferretti, and Asea (1997); and Mendoza and Tesar (1998).

Methodologically, our theoretical work builds on recent papers by Comin and Gertler (2006); Comin, Gertler, and Santacreu (2009); Kung and Schmid (2015); Corhay, Kung, and Schmid (2015); and Gavazzoni and Santacreu (2015). Following on the seminal work of Romer (1990) and Grossman and Helpman (1991), these papers integrate innovation-based endogenous growth models into the workhorse real business cycle model of macroeconomics. In contrast, our paper focuses on the role of government debt and taxation on investment, growth, and returns. In this sense, our paper is related to that of Croce, Nguyen, and Schmid (2012), who introduce fiscal policy into a simple stochastic endogenous growth model.

More broadly, our paper shares its focus with the growing literature on asset pricing in

general equilibrium models with production. We adopt recursive preferences, in the more recent spirit of Tallarini (2000); Campanale, Castro, and Clementi (2010); Kuehn (2008, 2009); Kaltenbrunner and Lochstoer (2010), as they all explore the relevance of priced endogenous consumption news shocks. Gourio (2012, 2013) examines disaster risks, a dimension which we consider relevant for future analysis on fiscal policy, but that is not part of our current analysis.

This paper is structured as follows. In section 2, we provide motivating empirical evidence linking movements in the government debt–to–GDP ratio to time-series patterns in stock returns. We develop a model to rationalize these findings in section 3. We calibrate the model in section 4 and provide novel predictions on the cross-sectional determinants of stock returns. We provide direct cross-sectional tests in the data in section 5. Section 6 concludes.

2 Empirical Analysis

In this section, we provide novel empirical evidence on the link between government debt, R&D-sorted stock returns, and growth. We begin by describing our data sources, and then discuss the results from our empirical asset-pricing tests.

2.1 Data Sources

Our empirical analysis links macroeconomic data with information on stock returns and firm-level fundamental accounting data. We use stock return data from CRSP and fundamental accounting data from COMPUSTAT to construct a combined panel at a quarterly frequency from 1975:Q1–2013:Q4. Our sample choice reflects the introduction of new accounting standards regarding the expensing of R&D costs by the Financial Accounting Standards Board (FASB) in 1975. For each calendar year, we construct stock return portfolios by sorting firms based on their R&D intensity. Our benchmark measure of intensity is the ratio of R&D expenses to total assets, as reported in COMPUSTAT. Our results also obtain when

we measure intensity as the ratio of R&D to capital expenditures (CAPEX), as in Lin (2012). Further results can be found in table A11 in the appendix.

We group firms into portfolios based on approximately even market capitalization. We consider both quintile and decile portfolios. We build our portfolios on the basis of market capitalization to ensure that the extreme portfolios are not driven by illiquid stocks. In our baseline case, the extreme portfolios constitute at least 10% of the total market capitalization. Equivalently, when forming portfolios, we choose our breakpoints so as to guarantee that both the top and the bottom R&D portfolio captures at least, and as closely to, ten percent of overall market capitalization as possible. This leaves us with an intermediate range of stocks comprising approximately eighty percent of overall stock market capitalization, that we either evenly distribute across the remaining eight portfolios, or consolidate in a portfolio that we denote as "Middle". Table A1 in the appendix gives a flavor of the industry composition of these portfolios. Our results are consistent with prior studies in the literature. We proceed analogously in case of quintile portfolios. In Table A2 in the appendix, we document that our main results also hold when we choose the extreme portfolios to consist of either the top or bottom twenty percent of firms.

We form these portfolios once for each year based on the previous year's R&D intensity and record both the equally-weighted (EW) and value-weighted (VW) return performance for the subsequent year. More specifically, letting indices i, j, and t represent portfolio i, stock j, and calendar year t respectively, we reassess the weights of each portfolio at the quarterly frequency. As a result, equally-weighted returns are constructed using the weighting scheme $w_{j,i,t} = 1/N_{i,t}$ where $N_{i,t}$ is the number of firms in a given portfolio in a given year. Value-weighted returns are computed using $w_{j,i,t+h/4} = \frac{V_{j,i,t+h/4}}{\sum_{j=1}^{N_{i,t}} V_{j,i,t+h/4}}$ for $h = 0, 1, 2, 3$ where $V_{j,i,t}$ is the market capitalization of firm j in portfolio i in period t.

Summary statistics of our extreme portfolios are reported in table 1. Consistent with prior findings, our R&D-intensive firms feature higher average excess returns, lower financial leverage, and lower sales-to-assets ratios than low-R&D-intensity firms. In the appendix,

Table 1: Portfolio Summary Statistics

	Low	High	*HML-R&D*
	Portfolio Returns		
Mean	22.07***	29.90***	7.84**
	(3.53)	(4.43)	(2.89)
Standard Deviation	24.38	30.61	19.99
Sample Size (number of quarters)	156	156	156
	Portfolio Characteristics		
Market Capital Share	10.06	11.19	21.25
R&D/Assets	0.14	85.80	42.96
Sales/Assets	3.11	0.13	1.62
Leverage	62	45	53
Average Number of Firms	586	632	

Notes: This table shows summary statistics for two R&D-sorted portfolios and the implied *HML-R&D* portfolio. Returns are equally-weighted and presented in annualized percentages. The average market capital share, R&D/Assets, Sales/Assets, and Leverage are presented in percentages. R&D/Assets is defined as annual research & development expenses divided by total assets and is used as our benchmark measure of R&D intensity. Our two extreme portfolios cover at least 10% of market capitalization. Sales/Assets is defined as annual net sales divided by total assets. Book leverage is defined as 1 - Tot. Equity/Tot. Assets. Our quarterly sample starts in 1975:Q1 and ends in 2013:Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

table A3, we report the corresponding results when we restrict our sample to firms with positive R&D, as often customary in empirical work on firm-level innovation (Chan, Lakonishok, and Sougiannis (2001)). In this case, our results arguably are even stronger, as the excess return spread on innovative firms almost doubles.

In our time series analysis, we use aggregate market returns from Kenneth French's website. For robustness, we also use the aggregate price-dividend ratio, obtained from Robert Shillers website, as well as market volatility. Quarterly market volatility is defined as the sum of squared monthly returns for a given quarter.

Our quarterly macroeconomic data are from the Federal Reserve Bank of St. Louis. All measures are seasonally adjusted. In what follows, we refer to the quarterly ratio of US debt relative to lagged GDP, as $DGDP$ ($DGDP_t = Debt_t/GDP_{t-1}$). GDP is real gross domestic product per the BEA (Series ID: GDPC96), and $DGDP$ serves as our main empirical measure

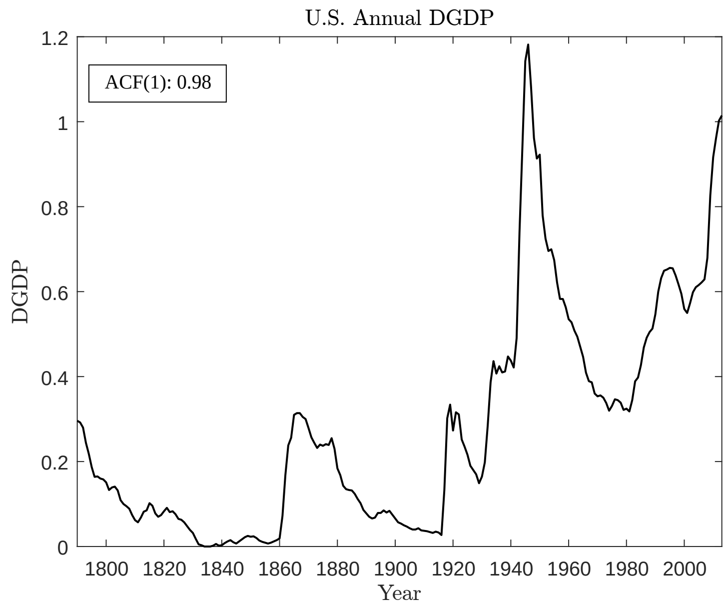

Fig. 1: U.S. Annual DGDP

Notes – This figure shows the ratio between public debt and lagged GDP ($DGDP$) in the US from 1790-2013. The first autocorrelation of this variable is denoted as $ACF(1)$ and reported in the top-left box.

for government's indebtedness. Our timing convention isolates innovations to debt from contemporaneous shocks to output that might drive a mechanical contemporaneous link between the debt-to-GDP ratio and risk premia. A similar specification has been used in Barro and Redlick (2011).

Figure 1 gives a graphical account of the evolution of $DGDP$ over a long sample starting in 1790. Clearly $DGDP$ has undergone long swings over time, peaking after World War II, and reaching similarly elevated levels again after the recent great recession. In line with this observation, we find a high annual autocorrelation of 0.98. The post-war mean of $DGDP$ is around 60 percent with a standard deviation of around 18 percent. Additional statistics for the other macroeconomic variables are discussed in section 4, where we assess the quantitative predictions of our model (see table 7).

2.2 Time-Series Asset Pricing Tests

Our motivating empirical evidence comes from standard predictive regressions of the form

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return on a particular portfolio.

Market. We start by noting that, consistent with the concurrent findings of Bai (2016) and Liu (2016), government debt predicts aggregate market returns significantly with a positive sign. For example, when we take $R_{t\to t+J}$ to be the excess return on the market portfolio, we find β^4_{DGDP} and β^8_{DGDP} to be 0.45 and 0.93, with standard errors of 0.08 and 0.12, respectively. We also find that these predictability result hold at shorter horizons, but they are statistically weaker. This finding suggests that times of high government indebtedness correspond to times of high aggregate risk premiums and are thus viewed as bad states of the world from the perspective of investors.

HML-R&D. Given our interest in links between government debt and innovation, we now turn to predictive return regressions for our cross section of portfolios sorted on firms' innovation intensity. We start by examining our extreme portfolios, namely the bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Table 2 documents our results for both equally- (upper panel) and value-weighted (lower panel) returns.

Intriguingly, $DGDP$ is not only an important predictor for market excess returns, but also for the cost of capital of innovation-intensive firms. Indeed we find that high levels of government debt also forecast higher expected returns for our *HML-R&D* portfolio. In other words, the cost of capital for innovative firms is especially sensitive to rises in government debt. These findings are robust across all forecast horizons for value-weighted returns and

Table 2: $DGDP$ and Predictability of Returns to Innovation

Horizon (J)	1	2	4	8	20
			EW		
Low-R&D	0.11***	0.18***	0.28***	0.41***	0.83
	(0.04)	(0.06)	(0.07)	(0.11)	(0.58)
R^2	0.00	0.00	0.01	0.02	0.08
High-R&D	0.16**	0.27***	0.49***	0.91***	3.15***
	(0.06)	(0.10)	(0.12)	(0.18)	(0.93)
R^2	0.01	0.02	0.04	0.09	0.39
HML-R&D	0.05	0.09	0.21**	0.49***	2.31***
	(0.05)	(0.09)	(0.10)	(0.16)	(0.61)
R^2	0.01	0.02	0.03	0.06	0.43
			VW		
Low-R&D	0.10**	0.16**	0.32***	0.57***	0.66
	(0.05)	(0.08)	(0.07)	(0.12)	(0.81)
R^2	0.01	0.02	0.04	0.07	0.01
High-R&D	0.22***	0.40***	0.77***	1.50***	3.56***
	(0.05)	(0.08)	(0.10)	(0.15)	(1.30)
R^2	0.05	0.08	0.14	0.30	0.36
HML-R&D	0.12***	0.24***	0.45***	0.93***	2.89***
	(0.04)	(0.07)	(0.08)	(0.12)	(0.85)
R^2	0.03	0.05	0.08	0.20	0.48

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return and $DGDP$ denotes the debt-to-output ratio. We report results for our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). In the top (bottom) panel, returns are equally-weighted (value-weighted). Innovation intensity is measured as the ratio of R&D expenses to total assets. Our quarterly sample is 1975:Q1–2013:Q4. Estimated coefficients have been adjusted with the Stambaugh bias correction. Bootstrap standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

become more significant for longer horizons in the case of equally-weighted returns.

In our appendix A, we report many detailed robustness checks that suggest that our baseline empirical results hold in many other settings and may be interpreted as conservative. In particular, our results are robust to varying the number of lags in the Newey-West adjusted standard errors (table A4), and to the inclusion of further predictive variables in

a multivariate setting (see our discussion of table A5).[1] In particular, our results are robust to inclusion of standard predictors such as the price-dividend ratio, market volatility, and the collective predictive power of a host of variables in the panel of Welch and Goyal (2008). Thus, we hereby identify $DGDP$ as a distinct predictor which is meaningful both statistically and economically.

In addition, we note that previous work has uncovered strong links between returns on R&D sorted portfolios and firms' financing constraints (Li (2011)). To account for the possibility that our results are driven by the presence of financial constraints, we follow Titman, Wei, and Xie (2004) and adjust our returns for commonly used indices for financial constraints, such as the KZ index (Kaplan and Zingales (1997)) and the SA index (Hadlock and Pierce (2010)), as well as leverage. In table A6, we show that our predictability results are robust to those adjustments as well.

In our baseline regressions, we consider all firms, including those that do not report any R&D expenditures. When we restrict our samples to positive R&D firms, our predictability results continue to be significant, regardless of whether we use equally-weighted returns (see tables A7 and A8) or value-weighted returns (see tables A9 and A10).

Entire cross section. After illustrating our stark results based on the *HML-R&D* portfolio, we now show that our findings extend to the entire cross-section of R&D sorted portfolios. To keep the inference sharp, rather than showing predictive regressions for each portfolio separately, we implement a parsimonious parameteric procedure that allows to jointly estimate the dependence of expected returns on $DGDP$ across all portfolios and horizons. More specifically, for both decile and quintile portfolios, we decompose the coefficient β^J_{DGDP} defined in the following regressions,

$$R_{i,t\to t+J} = \beta_{i,0} + \beta^J_{i,DGDP} DGDP_t + \epsilon_{i,t+J}, \tag{1}$$

[1] In the baseline case, we set the number of lags to four.

as follows

$$\beta^J_{i,DGDP} = \beta(J)[1 + \gamma(rd_i - \bar{rd})], \tag{2}$$

where rd_i is the time-series average of the R&D intensity of portfolio i; $\bar{rd}$ is the overall average of R&D intensity; and $\beta(J)$ is a horizon-specific coefficient. We then jointly estimate $\theta = (\beta(1), \beta(2), \beta(4), \beta(8), \beta(20), \gamma)$ in a GMM setting with the appropriate orthogonality restrictions implied by equation (1). This procedure allows us to decompose the predictive power of $DGDP$ into a horizon specific component, $\beta(J)$, and a cross-sectional R&D-sensitive component, γ. This approach easily accommodates additional predictive variables beyond $DGDP$ in a multivariate setting (see appendix C.1 for additional econometric details).

We report our results in table 3 for both decile and quintile portfolios, equally- and value-weighted returns, with and without additional controls. We find that the $\beta(J)$ coefficients are all highly statistically significant, and increasing with horizon. Moreover, the coefficient γ, which governs the extent of predictability across portfolios with different R&D-intensity, is estimated to be highly significant and positive in all specifications. This outcome reinforces the observation that portfolios with higher R&D intensity are more sensitive to movements in $DGDP$.

Figure 2 illustrates these patterns graphically. It displays the horizon specific β_{DGDP} across R&D intensity sorted portfolios, from simple unrestricted predictive regressions (dashed lines) as well as from the parameterized approach (solid lines) for the univariate approach. We note that the parameterized and the unrestricted estimates are rather close, thereby validating our procedure. Moreover, the figure clearly shows that the predictive coefficients are monotonically increasing in the portfolios $R\&D$ intensities, for any given horizons.

To summarize, our asset pricing tests show that innovative firms earn a time varying premium that rises with government indebtedness. In other words, the cost of capital for innovative firms increases with government debt, and more so than for more innovative firms.

Table 3: *DGDP* and Parameterized Regressions

	Benchmark Portfolios				5 Portfolios			
	Univariate		Multivariate		Univariate		Multivariate	
	EW	VW	EW	VW	EW	VW	EW	VW
γ	0.35***	0.37***	0.42***	0.35***	0.46***	0.34***	0.47***	0.32***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.06)	(0.06)	(0.06)	(0.07)
$\beta(1)$	0.12***	0.15***	0.08***	0.14***	0.11***	0.14***	0.09***	0.14***
	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
$\beta(2)$	0.2***	0.26***	0.15***	0.27***	0.2***	0.25***	0.17***	0.27***
	(0.02)	(0.05)	(0.02)	(0.04)	(0.02)	(0.03)	(0.01)	(0.04)
$\beta(4)$	0.36***	0.52***	0.26***	0.54***	0.35***	0.5***	0.28***	0.54***
	(0.03)	(0.07)	(0.02)	(0.07)	(0.03)	(0.06)	(0.02)	(0.06)
$\beta(8)$	0.61***	0.99***	0.43***	1.09***	0.59***	0.95***	0.46***	1.08***
	(0.03)	(0.07)	(0.04)	(0.07)	(0.05)	(0.08)	(0.03)	(0.08)
$\beta(20)$	1.64***	1.85***	1.47***	2.13***	1.4***	1.69***	1.39***	1.91***
	(0.04)	(0.05)	(0.06)	(0.04)	(0.11)	(0.12)	(0.09)	(0.15)

Notes: We report our estimates for the parameters reported in equations (1)–(2). Our quarterly sample is 1975:Q1–2013:Q4. 'Benchmark portfolios' refers to our decile portfolios. '5 Portfolios' refers to our quintile portfolios. Newey-West (1987) standard errors are in parentheses. In our multivariate regressions we control for both the aggregate price-dividends ratio and integrated market volatility. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

To the extent that innovative firms are engines of growth, rises in government debt may have implications for the real economy through its impact on their cost of capital. We examine this intuition in the next section.

2.3 Government Debt, R&D, and Growth

In this section we provide evidence on the effects of government debt on real economic activity both in the cross section of R&D intensity–sorted firms and in the aggregate.

***DGDP* and Investment.** We note that in the context of the endogenous growth model that we use in the next section, medium-term growth is linked to short-horizon fluctuations in investment expenditure. In this class of models, short-run fluctuations in innovation-oriented investments produce permanent effects on production levels and very long-lasting swings in

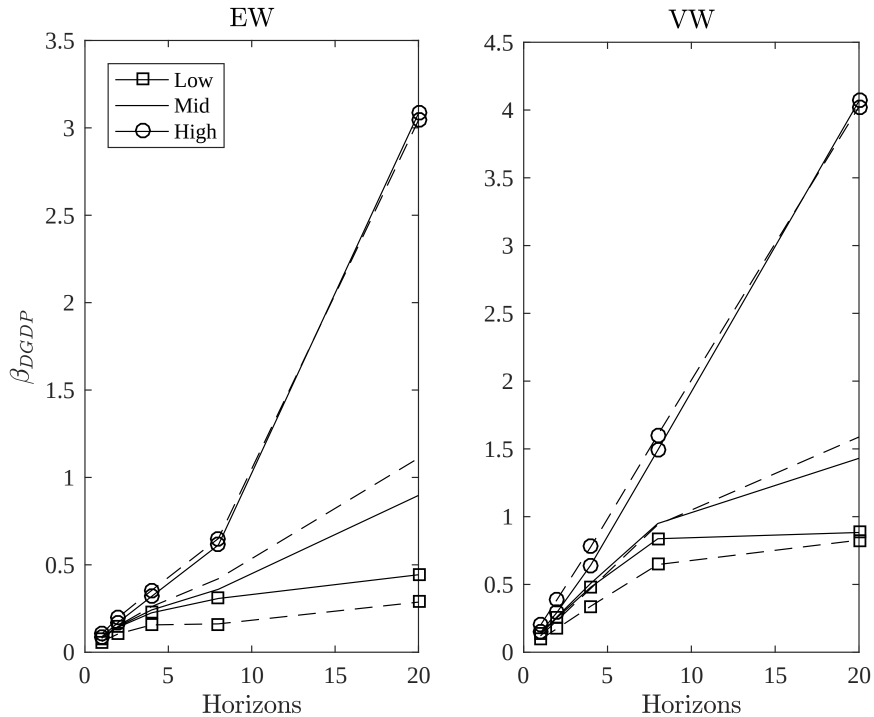

Fig. 2: Fitted Parameterized DGDP Coefficients

Notes – This figure shows fitted $\beta^{J}_{i,DGDP}$ coefficients as defined in equation (1) for our decile portfolios. The dashed lines refer to unrestricted OLS coefficients (see table 2). The solid lines indicate the estimates implied by the paramtetric form defined in equation (2) (see table 3).

future measured total factor productivity (TFP) growth (see, among others, Comin and Gertler (2006)). Given this consideration, we link quarterly and semi-annual innovations to $DGDP$ to the corresponding changes to the $I/R\&D$ ratio, where we use I to denote fixed tangible investment.[2] Specifically, we link $DGDP$ growth to investment growth, R&D growth, as well as the difference between investment and R&D growth. We work with the changes of these variables, as opposed to their levels, in order to address potential concerns about spurious regression results.

We present our main results in table 4. A novelty of our analysis is that it exploits variations at both the aggregate level (panel A) and among firms grouped in portfolios according to their R&D intensity (panel B). At a firm level, we use capital expenditure

[2]Real fixed tangible investment is derived from nominal gross private domestic investment (BEA account code A006RC1) less R&D expenditures (BEA account code Y694RC1Q027SBEA), and is deflated using the GDP deflator.

data from COMPUSTAT to measure physical investment. We do the same with R&D expenditures. All series are deflated using the GDP deflator.

Our first result is that an increase in government debt is associated with a decline in firms' investment both in R&D and in fixed assets. This obtains both at the aggregate (panel A) and at the firm (panel B) level, and with and without accounting for common controls. Critically, the drop in aggregate R&D investment dominates the reduction in aggregate capital expenditure (panle A, rightmost columns).[3]

Micro-data provide more details on the source of the reallocation (panel B). Specifically, given that in our baseline specification we include firms with no R&D expenditures, the reallocation naturally goes in the opposite direction for low-R&D firms. Firms with high R&D intensity, instead, promote a strong reallocation away from R&D when $DGDP$ increases. The corresponding significantly positive coefficient θ^A_{DGDP} for $\Delta I - \Delta R\&D$ is central to our analysis. Indeed, in the theoretical part of this manuscript we show that this reallocation channel can explain the empirical link between *HML-R&D* and $DGDP$.

We note that our aggregate results do not hold only in a univariate setting, but also obtain after controlling for productivity and government expenditure changes, i.e., two key exogenous variables in the context of the model that we introduce in the next section.[4] Through the lens of our model, an adjustment in $DGDP$ uncorrelated to productivity and government expenditure news can be interpreted as a pure shock to public financing, i.e., to the mix of taxation and deficits. When working with firm data aggregated to a portfolio level, we also control for measured Tobin's Q, a standard proxy for growth opportunities, as well as profitability. Equivalently, our channel is economically and statistically relevant even after we account for key firm characteristics used to predict investment growth.

[3] We first compute the difference of the raw investment growth rates and then standardize the resulting series.

[4] To avoid endogeneity issues, our control is quarterly utilization-adjusted productivity as in Fernald et al. (2012).

Table 4: Predicting Investment with $DGDP$

	$\Delta R\&D_{t+J}$				ΔI_{t+J}				$\Delta I_{t+J} - \Delta R\&D_{t+J}$			
Horizon J	1	2	1	2	1	2	1	2	1	2	1	2
Panel A: Aggregate Data												
	-0.26^{***}	-0.24^{***}	-0.24^{***}	-0.21^{***}	-0.16^{**}	-0.07	-0.04	0.09	0.07	0.15^{**}	0.15^{**}	0.25^{***}
	(0.06)	(0.06)	(0.07)	(0.08)	(0.08)	(0.09)	(0.07)	(0.09)	(0.07)	(0.08)	(0.07)	(0.08)
Controls			yes	yes			yes	yes			yes	yes
R^2	0.07	0.06	0.07	0.06	0.03	0.01	0.10	0.14	0.01	0.02	0.04	0.07
Panel B: Micro Data												
High-R&D	-0.15^{***}	-0.11^{**}	-0.18^{***}	-0.12^{**}	-0.19^{***}	-0.15^{**}	-0.22^{***}	-0.17^{**}	0.13^{***}	0.08^{*}	0.15^{***}	0.10^{**}
	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Controls			yes	yes			yes	yes			yes	yes
R^2	0.02	0.02	0.07	0.09	0.04	0.05	0.10	0.12	0.02	0.01	0.06	0.08
Low-R&D	-0.04	-0.12	-0.03	-0.11	-0.16	-0.25^{**}	-0.14	-0.24^{**}	-0.16^{*}	-0.26^{**}	-0.14	-0.25^{**}
	(0.07)	(0.11)	(0.07)	(0.11)	(0.09)	(0.11)	(0.10)	(0.11)	(0.09)	(0.11)	(0.10)	(0.11)
Controls			yes	yes			yes	yes			yes	yes
R^2	0.01	0.01	0.02	0.02	0.02	0.08	0.10	0.10	0.02	0.08	0.10	0.10

Notes: Panel A shows results from the following predictive regressions:

$$y_{t+1} = \theta_0 + \theta^A_{DGDP} \cdot \Delta DGDP_t + \text{controls}_t + \epsilon_{t+1}$$

where y_{t+1} is either aggregate R&D investment growth ($\Delta R\&D_t$), private domestic investment less R&D expenditures growth (ΔI_{t+1}), or the difference of these growth rates. $\Delta DGDP_t$ denotes debt-to-output ratio growth. Our control variables are the growth rates of aggregate utilization-adjusted productivity and government spending. Our quarterly sample starts in 1947:Q1 and ends in 2013:Q4. Panel B reports results from the following predictive regressions:

$$y^{\mathrm{k}}_{t+1} = \theta^{\mathrm{k}}_0 + \theta^{\mathrm{k}}_{DGDP} \cdot \Delta DGDP_t + \text{controls}^{\mathrm{k}}_t + \epsilon_{t+1}$$

where k refers to either our top-10 (High-R&D) or our bottom-10 (Low-R&D) portfolio, and y^{k}_{t+1} is either R&D investment growth, physical investment growth, or the difference of these growth rates at portfolio-level. We control for average portfolio-level Tobin's Q and cash flow profitability. Our COMPUSTAT quarterly sample starts in 1975:Q1 and ends in 2013:Q4. In both panels, Newey-West (1987) standard errors are in parentheses. All variables are standardized. In the rightmost column, we first compute the difference of the raw investment growth rates and then standardize the resulting series. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

***DGDP* and Growth.** It takes time for R&D investment to generate innovation and to be reflected in observable productivity and GDP growth. For this reason, in order to assess the impact of government debt on future growth, we focus on forecasting both measured TFP and output growth over longer horizons and report the results in table 5. We detail our construction of measured TFP in appendix C.2.[5]

In panel A, we report our findings from simple univariate regressions. Across all possible horizons, the debt-to-GDP ratio forecasts both output and TFP growth with a negative coefficient. These coefficients are statistically significant starting from a 6-month horizon and become highly statistically significant at horizons from two to five years. While the significance is appealing, the R^2s of these specifications is low. This result should not be surprising, given that strong adverse effects of government debt and fiscal variables on aggregate growth have been hard to identify in the data (see, for example, Easterly and Rebelo (1993), or Jaimovich and Rebelo (2017) for a recent discussion). The next panels of table 5 present novel empirical evidence of the existence of a negative link between government debt and growth through a risk-based mechanism.

In panel B and C, we link future growth rates to movements in the expected cost of capital specific to R&D-intensive firms, as measured by our forecasts of *HLM-R&D*. Since this portfolio has a short position in low-innovation stocks, the cost of capital of firms that are essentially out of the R&D segment of the economy is not included. Intuitively, it is natural to expect that the movements in the cost of capital of R&D-intensive firms are reflected in investment decisions, especially regarding R&D. When investment and innovation shape aggregate growth, variations in the cost of capital affect growth dynamics. Indeed, Croce, Nguyen, and Schmid (2012) formally demonstrate that in stochastic models in which growth is endogenously driven by investment in R&D there exists a negative link between growth and cost of capital. Panels B and C provide empirical evidence supportive of this theoretical prediction.

[5]Measured TFP is obtained as the Solow residual of the aggregate production function of our model (equation (24)).

Table 5: *DGDP* and Growth Predictability

Depend. Var.	Horizon J	1	2	4	8	20
Panel A: Growth Forecasts based on *DGDP*						
ΔGDP	(d_1^j)	-0.006	-0.011^{*}	-0.023^{**}	-0.044^{***}	-0.101^{***}
		(0.004)	(0.006)	(0.010)	(0.017)	(0.039)
R^2		0.018	0.025	0.034	0.042	0.055
ΔTFP	(d_1^j)	-0.004	-0.007^{*}	-0.015^{**}	-0.028^{**}	-0.080^{***}
		(0.003)	(0.004)	(0.007)	(0.013)	(0.029)
R^2		0.012	0.020	0.028	0.033	0.061
Panel B: Growth Forecasts based on *HML-R&D* (EW)						
ΔGDP	(c_1^j)	-0.026	-0.028^{***}	-0.044^{***}	-0.041^{***}	-0.020^{**}
		(0.037)	(0.077)	(0.034)	(0.213)	(0.041)
R^2		0.029	0.045	0.086	0.099	0.042
ΔTFP	(c_1^j)	-0.022	-0.023^{***}	-0.033^{***}	-0.036^{***}	-0.038^{***}
		(0.016)	(0.008)	(0.004)	(0.006)	(0.007)
R^2		0.033	0.057	0.102	0.144	0.148
Panel C: Growth Forecasts based on *HML-R&D* (VW)						
ΔGDP	(c_1^j)	0.010	-0.002	-0.041^{***}	-0.035^{**}	0.006
		(0.006)	(0.000)	(0.140)	(0.081)	(0.002)
R^2		0.003	0.005	0.091	0.045	0.052
ΔTFP	(c_1^j)	0.007	0.001	-0.023^{***}	-0.025^{**}	-0.004
		(0.012)	(0.013)	(0.009)	(0.010)	(0.010)
R^2		0.008	0.003	0.061	0.048	0.029

Notes: Panels A shows results from the following predictive regression:

$$\Delta Y_{t\to t+J} = d_0^J + d_1^J \cdot DGDP_t + w_{t+J},$$

where Y is either ΔGDP or ΔTFP and where $\Delta Y_{t\to t+J}$ denotes J-period cumulative variable growth. Panels B and C show look-ahead bias corrected results from the following predictive regression:

$$\Delta Y_{t\to t+J} = c_0^J + c_1^J \cdot \widehat{E}_t\left(R_{t\to t+J}^{HML-R\&D}\right) + c_2^J \cdot \widehat{\epsilon_{t+J}} + v_{t+J},$$

where expected excess returns cumulated over J quarters are obtained from the following predictive regression:

$$R_{t\to t+J}^{HML-R\&D} = \beta_0^J + \beta_{DGDP}^J \cdot DGDP_t + \beta_{PD}^J \cdot PD_t + \beta_{MV}^J \cdot MV_t + \epsilon_{t+J}.$$

Portfolios are formed based on innovation intensity, measured as R&D investment expenses divided by total value of assets. Our quarterly sample is 1975:Q1–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

These results are significant at medium and longer horizons. Furthermore, our findings hold regardless of whether we use equally-weighted or value-weighted results. Using forecasts of equally-weighted *HML-R&D* returns leads to substantial gains in explanatory power, especially for measured TFP.[6] These gains corroborate the relevance of our risk-based mechanism.

These patterns linking debt, innovation, and risk premia motivate us to develop a formal R&D-based production economy model in order to link fiscal policy risks and growth and provide a structural interpretation of our empirical results.

3 An Asset-Pricing Model with Debt and Innovation

We link public debt and innovation by developing a stochastic endogenous growth model in which a government finances exogenous expenditures by issuing public debt and taxing firms. Our baseline framework adds fiscal policy rules in the spirit of Croce, Nguyen, and Schmid (2012) to a stochastic model of endogenous growth with recursive preferences proposed by Kung and Schmid (2015).

In the model, sustained growth arises endogenously through the accumulation of patented intermediate goods (henceforth patents) that facilitate the production of a final consumption good. New patents are created through innovation requiring investment in research and development and can be stored. In this model, therefore, patents represent an endogenous stock of intangible capital. The model also features physical capital and can be used to study a cross section of returns sorted according to R&D intensity.

We start by introducing the government's fiscal stance. We proceed by describing in detail the production sector and the innovation process in our economy, after which we present the household sector and define the general equilibrium.

[6]We thank an anonymous referee suggesting this specification.

3.1 Government

We assume that the government faces an exogenous and stochastic expenditure stream, G_t, that evolves as follows:

$$\frac{G_t}{GDP_t} = \frac{1}{1 + e^{-gy_t}}, \tag{3}$$

where

$$gy_t = (1 - \rho_G)\overline{gy} + \rho_G gy_{t-1} + \epsilon_{G,t}, \quad \epsilon_{G,t} \sim N(0, \sigma_G^2). \tag{4}$$

This specification ensures that $G_t \in (0, GDP_t)$ for all date t, and it enables us to replicate key features of the expenditure-to-output ratio observed in the US data. In most of our analysis, we focus only on the expenditure component of total public liabilities and abstract away from entitlements. GDP_t arises endogenously from the production process, and we describe its components in detail below.

We assume that the government can finance these expenditures by raising public debt or by levying distortionary profit taxes on corporations, at a possibly time-varying rate τ_t. When doing so, the government is subject to the following budget constraint:

$$B_t = (1 + r_{f,t-1})B_{t-1} + G_t - T_t, \tag{5}$$

where $T_t = \tau_t \cdot tax\,base_t$ denotes its total tax income. We specify the components of the tax base below.

The government's fiscal stance accommodates taxation and deficit financing through simple, implementable, and plausible fiscal rules, in the spirit of Favero and Monacelli (2005), Schmitt-Grohe and Uribe (2007), Bi and Leeper (2010), and Leeper, Plante, and Traum (2010). In this paper we focus on a tax rule that allows for tax smoothing and lets the government adjust its fiscal stance according to prevailing macroeconomic conditions. We focus on two aspects of tax smoothing, namely the persistence and intensity of swings in the tax rate. We specify the government's policy in terms of a debt management rule, with tax

rates implied by the budget constraint, as follows:

$$\frac{B_t}{GDP_t} = (1-\rho_B)\mu_B + \rho_B \frac{B_{t-1}}{GDP_{t-1}} + \epsilon_t^B, \tag{6}$$

$$\epsilon_t^B = A_\omega \epsilon_{\omega,t} + A_G \epsilon_{G,t} + A_\phi \epsilon_{\phi,t}, \tag{7}$$

where A_ω, A_G and A_ϕ are constant parameters that determine both the intensity and cyclicality of the government response to shocks; $\epsilon_{\omega,t}$ is a productivity shock; and $\epsilon_{\phi,t} \sim i.i.d.N(0,1)$ is a pure policy shock. In what follows, we show that policy shocks are relevant in bringing the model closer to the data. The parameter μ_B captures the long-run level of debt, and $\rho_B \in (0,1)$ is a measure of the speed of repayment of debt: the higher the value of ρ_B, the slower the repayment of debt relative to output.

This parsimonious specification has two main advantages. First, the condition $\rho_B < 1$ guarantees that the debt-output ratio remains stationary, consistent with the evidence in Bohn (1998). In the language of Bi and Leeper (2010), our rule in equation (6) anchors expectations about future debt and rules out unstable paths. Second, this specification replicates key empirical properties of the US debt-output ratio.

3.2 Production

The production process involves three sectors. The final consumption good is produced in a competitive sector, namely the final-goods sector, using physical capital, labor, and patents. Stationary shocks drive stochastic fluctuations in the production of the final consumption good. Patents are produced in the intangible sector, where firms have monopoly power. New patents are created by means of innovation through R&D in the competitive innovation sector, which determine the speed of growth.

Regarding taxation, we assume that profits in both the final-goods sector and the intangible sector are taxed at the rate τ_t. In this setup, taxes distort firms' investment and innovation decisions, and hence the rate and the dynamics of growth.

Final-Goods Sector. There is a representative firm that uses capital K_t, labor L_t, and a composite of patents Γ_t to produce the final (consumption) good according to the production technology

$$Y_t = (K_t^{\alpha}(\Omega_t L_t)^{1-\alpha})^{1-\xi}\Gamma_t^{\xi}, \tag{8}$$

where the composite Γ_t is defined as

$$\Gamma_t \equiv \left[\int_0^{N_t} X_{i,t}^{\nu}\, di\right]^{\frac{1}{\nu}}, \tag{9}$$

and $X_{i,t}$ is the quantity of patents $i \in [0, N_t]$. N_t is the measure of patents in use at date t, α is the physical capital share, ξ is the intangible capital share, and the elasticity of substitution between patents is $\frac{1}{1-\nu}$ with $\nu < 1$. We interpret N_t as the stock of intangible capital.

We introduce uncertainty into the model by means of an exogenous stochastic process Ω_t affecting the level of output. Importantly, we assume that Ω_t follows a stationary Markov process by specifying that $\Omega_t = e^{a_t}$, and $a_t = \rho a_{t-1} + \epsilon_{\omega,t}$, with $\epsilon_{\omega,t} \sim N(0, \sigma^2)$ and $\rho < 1$. Because the forcing process is stationary, sustained growth arises endogenously from the development of new patents. We describe how new patents are developed by means of innovation below.

The firm's objective is to maximize shareholder value. This can be formally stated as

$$\max_{\{I_t, L_t, K_{t+1}, X_{i,t}\}_{t\geq 0, i\in[0,N_t]}} E_0\left[\sum_{t=0}^{\infty} M_t D_t\right],$$

where the firm's dividends are

$$D_t = (1-\tau_t)\left[Y_t - W_t L_t - \int_0^{N_t} P_{i,t} X_{i,t}\, di\right] - I_t. \tag{10}$$

Here, M_t is the stochastic discount factor, I_t is investment in physical capital, W_t is the wage rate, and $P_{i,t}$ is the price per unit of patent i at time t. Prices $P_{i,t}$ are set by patent

producers in the intangible sector, while the stochastic discount factor and the wage rate are determined in the general equilibrium and are all taken as given by the final-goods firm. The final-goods firm's profits are taxed at the rate τ_t.

In line with the literature on production-based asset pricing, we assume that investment is subject to convex capital adjustment costs, so that the physical capital stock evolves as

$$K_{t+1} = (1-\delta)K_t + \Lambda\left(\frac{I_t}{K_t}\right)K_t. \tag{11}$$

Here, δ is the depreciation rate of physical capital and $\Lambda(\cdot)$ the capital adjustment cost function. We specify $\Lambda(\cdot)$ as in Jermann (1998), $\Lambda\left(\frac{I_t}{K_t}\right) \equiv \frac{\alpha_1}{\zeta}\left(\frac{I_t}{K_t}\right)^{\zeta} + \alpha_2$, where $\frac{1}{1-\zeta}$ represents the elasticity of the investment rate with respect to Tobin's Q. The parameters α_1 and α_2 are set so that there are no adjustment costs in the deterministic steady state.

Intangible Sector. Patents are produced in the intangible sector. Patent producers have monopoly power. Given the demand schedules set by the final-good firm, monopolists producing the patents set the prices $P_{i,t}$ in order to maximize their after-tax profits $(1-\tau_t)\Pi_{i,t}$. Patent producers transform one unit of the final good into one unit of their patent. This fixes the marginal cost of producing one patent at unity. Further, production is "roundabout" in that monopolists take final-goods production as given, as they are tiny themselves.

Thus, monopolists solve the following static profit-maximization problem each period:

$$\max_{P_{i,t}}(1-\tau_t)\Pi_{i,t} \equiv \max_{P_{i,t}}(1-\tau_t)(P_{i,t}\cdot X_{i,t}(P_{i,t}) - X_{i,t}(P_{i,t})).$$

The value $V_{i,t}$ of owning exclusive rights to produce patent i is equal to the present discounted value of the current and future monopoly net profits,

$$V_{i,t} = (1-\tau_t)\Pi_{i,t} + (1-\phi)E_t[M_{t+1}V_{i,t+1}], \tag{12}$$

where ϕ is the probability that a patent becomes obsolete. This asset price is important in our model, as it provides the payoff for creating new patents by means of innovation. Indeed, thanks to monopoly power, the associated profits provide the rents required to support innovation.

Innovation Sector. Innovators develop new patents used in the production of final output. They do so by conducting research and development, using the final good as input at unit cost. These newly developed patents can be sold to patent producers. Assuming that this market is competitive, the price of a new patent will equal its value to the patent producer, namely $V_{i,t}$.

We link the evolution of the intangible capital stock N_t, to innovation as follows:

$$N_{t+1} = \vartheta_t S_t + (1-\phi) N_t, \tag{13}$$

where S_t denotes R&D expenditures (in terms of the final good) and ϑ_t represents the productivity of the R&D sector that is taken as exogenous by the R&D sector. In the spirit of Comin and Gertler (2006), we assume that this technology coefficient involves a congestion externality effect

$$\vartheta_t = \frac{\chi \cdot N_t}{S_t^{1-\eta} N_t^{\eta}}, \tag{14}$$

where $\chi > 0$ is a scale parameter and $\eta \in [0,1]$ is the elasticity of new patents with respect to R&D. This specification captures the notion that concepts already discovered make it easier to come up with new ideas, $\partial\vartheta/\partial N > 0$, and that R&D investment has decreasing marginal returns, $\partial\vartheta/\partial S < 0$.[7]

[7]Similarly, this congestion externality can be thought of as giving rise to adjustment costs to investment in intangible capital, that is, R&D. We will later see that the optimality condition for R&D is $\frac{1}{\vartheta_t} = E_t[M_{t+1}V_{t+1}]$. Absent the congestion externality, this becomes $1 = E_t[M_{t+1}V_{t+1}]$, a result analogous to q-theory, in which case the absence of adjustment cost fixes marginal Q at unity.

3.3 Household

The household sector is standard. The representative household has Epstein-Zin preferences defined over consumption:

$$U_t = \left\{(1-\beta)C_t^{\theta} + \beta(E_t[U_{t+1}^{1-\gamma}])^{\frac{\theta}{1-\gamma}}\right\}^{\frac{1}{\theta}}, \tag{15}$$

where γ is the coefficient of relative risk aversion and $\psi \equiv \frac{1}{1-\theta}$ is the intertemporal elasticity of substitution. When $\psi \neq \frac{1}{\gamma}$, the agent cares about news regarding long-run growth prospects. We assume that $\psi > \frac{1}{\gamma}$ so that the agent has a preference for early resolution of uncertainty and dislikes shocks to long-run expected growth rates.

The household maximizes utility by participating in financial markets and by supplying labor. Specifically, the household can take positions $\mathcal{Z}_t$ in the stock market, which pays an aggregate dividend $\mathcal{D}_t$, and positions B_t in the bond market. Accordingly, the budget constraint of the household becomes

$$C_t + \mathcal{Q}_t\mathcal{Z}_{t+1} + B_{t+1} = W_tL_t + (\mathcal{Q}_t + \mathcal{D}_t)\mathcal{Z}_t + (1 + r_{f,t})B_t,$$

where $\mathcal{Q}_t$ is the stock price, $r_{f,t}$ is the risk-free rate, W_t is the wage, and L_t denotes hours worked.

We assume that stocks are claims to all the production sectors, namely the final-goods sector, the intangible sector, and the R&D sector. Accordingly, we define the aggregate dividend as the net payout from all production sectors:

$$\mathcal{D}_t = D_t + \int_0^{N_t}(1-\tau_t)\Pi_{i,t}\,di - S_t. \tag{16}$$

3.4 Equilibrium and Asset Prices

An equilibrium is a set of sequences of prices and quantities such that (i) quantities solve producers' and the household's optimization problems, and (ii) prices are such that the markets clear. We focus on a symmetric equilibrium in which all patent producers are identical. In the following, we describe the most important equilibrium conditions.

The final-good firm's optimality conditions are mostly standard. Denoting by $q_t = \frac{1}{\Lambda'_t}$ the shadow value of physical capital, the first-order condition for investment in physical capital implies

$$\begin{aligned} R_{t+1} &:= \frac{1}{q_t}\left((1-\tau_{t+1})\alpha(1-\xi)\frac{Y_{t+1}}{K_{t+1}} + q_{t+1}(1-\delta) - \frac{I_{t+1}}{K_{t+1}} + q_{t+1}\Lambda_{t+1}\right), \\ 1 &= E_t\left[M_{t+1}R_{t+1}\right]. \end{aligned} \tag{17}$$

On the other hand, the final-good firm's demand for patent i is determined by

$$P_{i,t} = (K_t^{\alpha}(\Omega_t L_t)^{1-\alpha})^{1-\xi}\frac{\xi}{\nu}\left[\int_0^{N_t} X_{i,t}^{\nu}\, di\right]^{\frac{\xi}{\nu}-1} \nu X_{i,t}^{\nu-1},$$

where it takes the price $P_{i,t}$ as given. The latter is set by the monopolistically competitive producer of patent i. In a symmetric equilibrium, the Dixit and Stiglitz (1977) monopolistically competitive characterization of the intangible sector implies

$$X_{i,t} \equiv X_t, \quad \text{and} \quad P_{i,t} \equiv P_t = \frac{1}{\nu}. \tag{18}$$

That is, each patent producer charges a markup $\frac{1}{\nu} > 1$ over unit marginal cost, so that profits are

$$\Pi_{i,t} \equiv \Pi_t = \left(\frac{1}{\nu} - 1\right) X_t, \tag{19}$$

with $X_t = \left(\xi\nu\left(K_t^{\alpha}(\Omega_t L_t)^{1-\alpha}\right)^{1-\xi} N_t^{\frac{\xi}{\nu}-1}\right)^{\frac{1}{1-\xi}}$. Profits are thus procyclical.

Discounted future profits on patents are the payoff for innovation, so that, since the R&D sector is competitive, the optimality condition for R&D investment becomes

$$E_t[M_{t+1}V_{t+1}](N_{t+1} - (1-\phi)N_t) = S_t, \tag{20}$$

in which case the expected sales revenues equals costs, or equivalently, at the margin,

$$\frac{1}{\vartheta_t} = E_t[M_{t+1}V_{t+1}].$$

This condition is crucial in this model, as it sets the equilibrium amount of R&D investment and ultimately determines the equilibrium growth rate of the economy. Importantly, R&D investment inherits the procyclicality of profits.

The stochastic discount factor in the economy is given by

$$M_{t+1} = \beta\left(\frac{C_{t+1}}{C_t}\right)^{\theta-1}\left(\frac{U_{t+1}}{E_t(U_{t+1}^{1-\gamma})^{\frac{1}{1-\gamma}}}\right)^{1-\gamma-\theta}, \tag{21}$$

where the second term involves continuation utilities and captures concerns about long-run growth prospects. Optimality implies the following asset pricing conditions:

$$\begin{aligned} \mathcal{Q}_t &= E_t[M_{t+1}(\mathcal{Q}_{t+1} + \mathcal{D}_{t+1})] \\ \frac{1}{1+r_{f,t}} &= E_t[M_{t+1}]. \end{aligned} \tag{22}$$

In equilibrium, the representative agent holds the entire supply of both bonds and equities. The latter is normalized to be one, that is, $\mathcal{Z}_t = 1\ \forall t$.

Finally, since the agent has no disutility for labor, she will supply her entire endowment, which we normalize to unity.

Resource Constraint. Final output is used for consumption and investment in physical capital and is used as a factor input in R&D, the production of patents, and government expenditures:

$$\begin{aligned} Y_t &= C_t + I_t + N_t X_t + S_t + G_t \\ &= C_t + I_t + N_t^{1-\frac{1}{\nu}} \Gamma_t + S_t + G_t, \end{aligned}$$

where the second equality exploits the optimality conditions and the term $N_t^{1-\frac{1}{\nu}}\Gamma_t$ captures the costs of patent production. Given that $\nu < 1$ reflects monopolistic competition, it follows that a growing intangible capital stock increases the efficiency of patent production, since the costs fall as N_t grows.

Given the resources used in the production of patents, in our economy measured GDP_t is obtained as follows:

$$GDP_t \equiv Y_t - N_t X_t. \tag{23}$$

Finally, the tax base is given by taxable profits in both final-goods and intangible sectors, so that

$$\begin{aligned} tax\, base_t &= Y_t - W_t L_t - N_t \nu^{-1} X_t + N_t \Pi_t \\ &= GDP_t - W_t L_t. \end{aligned}$$

Stock Market and Cross Section. According to equation (22), the ex-dividend value of the stock market value, $\mathcal{Q}_t$, is the discounted sum of future net payouts of all production sectors. In our symmetric equilibrium, we have

$$\mathcal{D}_t = (1 - \tau_t)\left[GDP_t - W_t L_t\right] - S_t - I_t.$$

The existence of two capital stocks, namely those of physical and intangible capital, gives

rise to a cross section of stock returns in our model. For empirical purposes, we associate the return on tangible (intangible) capital, with the empirical returns of Low-R&D (High-R&D) firms. In the model, the return of intangible capital is

$$R_t^{rd} = \frac{V_t}{V_{t-1} - (1-\tau_t)\Pi_t},$$

and that of physical capital is defined in equation (17). While clearly not unique, we view this mapping as natural and economically meaningful.

3.5 Aggregate Productivity Growth and Fiscal Policy

The previous paragraphs have outlined a stochastic equilibrium model in which innovation through firms' R&D drives long-term growth rates. Let us briefly describe how, in the context of the model, government debt and fiscal policy affect innovation and thus growth. Following Kung and Schmid (2015), it can be shown that under the parameteric restriction $\alpha + \frac{\frac{\xi}{\nu}-\xi}{1-\xi} = 1$, which we impose in the following, the model is equivalent to a real business cycle model with a standard neoclassical production function of the form $Y_t = Z_t K_t^{\alpha} L_t^{1-\alpha}$, where

$$Z_t \equiv \overline{A}(\Omega_t N_t)^{1-\alpha}, \tag{24}$$

is an endogenous productivity process, with $\overline{A} \equiv (\xi\nu)^{\frac{\xi}{(1-\xi)}} > 0$. In other words, our model can be seen as a real business cycle model in which productivity is endogenously driven by the accumulation of intangible capital via innovation. Taxation thus directly affects growth and its dynamics through its effects on the demand for intangible capital.

Two channels shape the accumulation of intangible capital. First, the final-good firm's demand for patents, pinned down by the first order condition with respect to $X_{i,t}$, namely $P_{i,t} = (K_t^{\alpha}(\Omega_t L_t)^{1-\alpha})^{1-\xi} \frac{\xi}{\nu} \left[\int_0^{N_t} X_{i,t}^{\nu}\, di\right]^{\frac{\xi}{\nu}-1} \nu X_{i,t}^{\nu-1}$, depends positively on the capital stock, whose accumulation itself is affected by taxation. By slowing down capital accumulation,

taxation also depresses innovation and growth. Second, taxation affects the valuation of patents, as the value of a patent is given by $V_{i,t} = (1 - \tau_t)\Pi_t + (1 - \phi)E_t[M_{t+1}V_{i,t+1}]$. Higher taxes thus depress patent valuations, and this lowers the incentives to engage in innovation, as the value of patents is the payoff for R&D.

To summarize, in our model with stochastic endogenous growth, higher taxes and the expectation of an elevated tax burden going forward depress firms' incentives to engage in innovation, thereby curtailing growth prospects. Since tax rates in our model reflect both the government's expenditures and its indebtedness through its budget constraint, we expect the model to generate predictions regarding the links between debt, growth, and innovation. We examine these predictions quantitatively in the next section.

4 Quantitative Analysis

In this section we calibrate our model and explore its predictions regarding key links between debt, innovation, and stock returns in the cross section and the time series. In particular, we show that the model predicts a reallocation effect across the R&D and non-R&D sectors that is sensitive to the level of the debt-to-output ratio, which helps interpreting the time-varying *HML-R&D* spread documented empirically.

4.1 Calibration

We report our baseline quarterly calibration in table 6. The preference parameters are standard in the literature. The risk aversion (γ) is calibrated to 10 in line with reasonable upper bounds (see Mehra and Prescott (1985), among others). The intertemporal elasticity of substitution (ψ) is set to 1.2, a choice consistent with the empirical results in the long-run risk literature. The household's subjective discount rate is chosen to target the average historical level of the risk-free.

In the R&D sector, we set the quarterly survival rate ϕ of a patent to 0.96, consistent

Table 6: Benchmark Calibration

Parameter	Symbol	Value
Preferences:		
Subjective Discount Factor	β	0.996
Intertemporal Elasticity of Substitution	ψ	1.2
Relative Risk Aversion	γ	10.0
Technology:		
Labor Income Subshare	α	0.42
Intangible Capital Income Share	ξ	0.47
Intangible Capital Congestion, Scale Parameter	χ	0.45
Intangible Capital Congestion, Elasticity	η	0.83
Patent Survival Rate	ϕ	0.96
Physical Capital Depreciation	δ	0.02
Physical Capital Adjustment Costs, Elasticity	ζ	13.30
Elasticity of Substitution Across Goods	ν^{-1}	1.65
Exogenous Processes:		
Productivity Shock, Volatility	σ_ω	0.02
Productivity Shock, Persistence	ρ	0.99
Average Expenditure-Output Ratio	$1/(1+e^{-\overline{gy}})$	0.20
Expenditure Shock, Volatility	σ_G	0.08
Expenditure Shock, Persistence	ρ_G	0.98
Policy Parameters:		
Average Quarterly Debt-GDP Ratio	μ_B	2.40
Persistence of Debt-GDP	ρ_B	0.99
Policy Response to Productivity Shock	A_ω	-0.56
Policy Response to Expenditure Shock	A_G	0.45
Policy Response to Policy Shock	A_ϕ	0.07

	Model		Data	
	$\mu_B/4$ =60%	$\mu_B/4$ =30%	Est.	Std. Err.
a_2	-0.13	-0.13	-0.18^{*}	0.10
a_3	0.16	0.16	0.21^{***}	0.05
$\sigma(\epsilon_t^{DGDP})$	0.02	0.02	0.01^{***}	0.001

Notes: This table reports our benchmark quarterly calibration. In the bottom portion, we report results from the following auxiliary regression:

$$DGDP_t = a_0 + a_1 DGDP_{t-1} + a_2 \widehat{\epsilon_t^{\Delta TFP}} + a_3 \widehat{\epsilon_{G,t}} + \epsilon_t^{DGDP},$$

where $\widehat{\epsilon_t^{\Delta TFP}}$ is the fitted residual from the regression $\Delta TFP_t = b_0 + b_1 \Delta TFP_{t-1} + \epsilon_t^{\Delta TFP}$, and $\widehat{\epsilon_{G,t}}$ is obtained by estimating equations (3)–(4). Our quarterly sample starts in 1975:Q1 and ends in 2013:Q4. In the model, *TFP* is measured as in equation (24).

with the Bureau of Economic Analysis (BEA) annual depreciation rate for R&D capital of 16%. The elasticity of new intermediate goods with respect to R&D (η) is set to the value

reported in Croce, Nguyen, and Schmid (2012). Furthermore, our choice of η is within the range of panel and cross-sectional estimates from Griliches (1990). χ is a scale parameter that is set to match an average annual consumption growth of 2.0%.

As shown in our empirical analysis, low-R&D firms command a lower risk premium than R&D-intensive firms. In order to reproduce this fact, we set the elasticity of the adjustment cost function (ζ) to 13.3. The elasticity of substitution between intermediate goods (ν) is set to capture the fact that the level of productivity in the final-goods sector is increasing. The parameter α determines the average income share of physical capital. The annualized depreciation rate of physical capital (δ) is set to 8%.

We target specific moments in the US sample for the post-World War II period 1947:Q1-2013:Q4. Specifically, we set the volatility of our productivity shocks to match an annual volatility of consumption growth of about 2%. The persistence of productivity is chosen so as to have a positive but small autocorrelation in consumption growth. In a similar spirit, the average level, the volatility, and the persistence of the ratio of government expenditure to output are set to replicate US quarterly data. Specifically, we transform the US measured government-output ratio according to equation (3) and estimate equation (4), with the following results:

$$gy_t = -\underset{(0.05)}{1.32} \cdot [1 - 0.96] + \underset{(0.02)}{0.96} gy_{t-1} + \underset{(0.02)}{0.06} \epsilon_{G,t}.$$

Numbers in parentheses are standard errors. Our parameter values are within our empirical confidence intervals.

Turning our attention to the the fiscal policy rule, the average annual debt-to-output ratio is set to 60%, as in the data.[8] In the next section we also consider a fiscal regime with an average debt-to-output ratio of 30%. The parameter ρ_B is set to mimic the well-known high persistence of the debt-to-output ratio in the US.

The other parameters of the systematic part of our fiscal rule, A_ϕ and A_G, are chosen so

[8] The standard error of this estimate is very moderate, 1.51%.

that the government expands its debt financing in response to either negative technology or positive government spending shocks. Thus, our government implements a countercyclical debt policy in an attempt to attenuate the tax burden on corporations in downturns.

In order to have quantitative guidance on these parameters, we project innovations in the US debt-output ratio on innovations to both TFP growth and government expenditure–to–output. In the model, the correct counterpart of measured TFP is obtained by simulating equation (24). By running our auxiliary regression in the model exactly as we do in the data, we mitigate concerns about identification of pure exogenous fiscal shocks. As shown in the bottom portion of table 6, our calibration is consistent with our auxiliary regression, that is, it captures the right amount of coutercyclicality.[9]

Since the standard deviation of the fiscal policy shocks is normalized to one, the parameter A_ϕ determines the magnitude of the policy shocks, and it is set to replicate the volatility of the debt-to-output ratio.

4.2 Findings

We start by evaluating the overall fit of the model in regard to stylized facts about economic growth, cycles, and asset returns, and then turn to a more detailed discussion of the cross-sectional and time-series links between debt, innovation, and returns, motivated by our empirical evidence.

Unconditional Moments. In table 7 we report basic moments from model simulations, both for quantities and for returns. We show results from both our benchmark calibration and an alternative calibration in which the average debt-to-output ratio is set to 30%, and compare them to our empirical moments.

Our model is broadly quantitatively consistent with basic patterns of real aggregates,

[9] We focus on the post-1975 sample for consistency with our analysis of COMPUSTAT data. This choice is not crucial because the empirical estimates of this auxiliary regression are nearly unchanged when we consider also pre-1975 data.

Table 7: **Model Summary Statistics**

	Data	SE	Model 60%	Model 30%
$E[\Delta C]$	2.08	0.20	1.95	2.06
$ACF(\Delta C)$	0.09	0.16	0.38	0.38
$\sigma(\Delta C)$	1.66	0.14	2.07	2.06
$\sigma(\Delta I)$	11.40	0.70	8.73	8.53
$\sigma(\Delta S)$	3.11	0.34	10.56	10.20
$\sigma(\Delta GDP)$	1.92	0.14	2.63	2.62
$E[R^{rd} - R]$	7.84	3.20	3.32	2.67
$\sigma(R^{rd} - R)$	19.93	2.33	4.03	3.71
$E[\tau]$	31.95	1.40	35.44	35.98
$\sigma(\tau)$	12.80	4.08	17.33	17.00
$\theta^A_{DGDP} = \frac{\partial \Delta \log(I/S)}{\partial \Delta DGDP}$	0.15	0.07	0.05	0.02

Notes: This table shows annualized model statistics for the scenarios in which the debt-to-GDP ratio is on average either 60% or 30%. Statistics are obtained from a long-sample simulation. The entries for the data moments are based on aggregate data provided in the NIPA tables, for the sample 1947:Q1-2013:Q4. Quarterly consumption growth is constructed from real per capita non-durables and services expenditure. Quarterly physical investment growth (ΔI) is constructed from gross fixed private domestic investment less R&D expenditures. R&D growth (ΔS) is constructed from quarterly R&D expenditures, as reported by the BEA. All investment series are deflated using the GDP deflator. Government spending-to-GDP ($Govt/GDP$) comprises current government expenditures. GDP is real gross domestic product per the BEA (Series ID: GDPC96). $DGDP$ is constructed by dividing total public debt by lagged GDP. In the data, $R^{rd} - R$ refers to the *HML-R&D* portfolio return over the sample 1975:Q1-2013:Q4. In the model, we use the excess return of the R&D sector over that of the physical capital sector in log units levered by a coefficient of three. The corporate tax rate (τ) is constructed as in McGrattan and Prescott (2005) by focusing on non-financial corporations over the annual sample (1929-2013). θ^A_{DGDP} represents the estimated coefficient from the aggregate predicted regression in Table 4. Means and standard deciations have been multiplied by 100.

such as output, consumption, and investment, as well as innovation and endogenous growth. Consumption is realistically smooth with low autocorrelation, implying that our model does not generate an implausibly high variation in long-run growth, consistent with the data. As in the data, both investment in R&D and physical capital are more volatile than output. These results are relevant, because models with innovation-driven endogenous growth face additional challenges in matching the average growth rate, above and beyond those in a standard real business cycle model.

Through the government budget constraint, our calibration implies an average tax rate

of 35% and a volatility of about 17% percent, in line with the estimates in McGrattan and Prescott (2005) after we include pre–World War II data.

Our model yields a realistic spread between the excess returns on intangible and tangible capital, that is, the counterpart of our *HML-R&D* return. As in the data, R&D-intensive firms earn a positive premium relative to physical capital–intensive firms.

The last entry in table 7 reports the regression coefficient, θ^A_{DGDP}, obtained from projecting the relative change in investment versus R&D, $\Delta I - \Delta R\&D$, on current $DGDP$, analogous to the empirical specification in table 5, panel A. As in the data, we confirm that the model gives rise to $\theta^A_{DGDP} > 0$, indicating that while both aggregate investment and R&D decline upon rises in $DGDP$, physical investment drops relatively less. In other words, our model generates a quantitatively relevant reallocation effect towards physical investment in response to increases in $DGDP$. Furthermore, untabulated simulation results confirm that low (high) I_t/S_t episodes are associated with high (low) expected market excess returns in the model. This is consistent with the empirical evidence in Lin (2012).

Fiscal Policy Regimes. Inspection of the rightmost panel of table 7 paves the way to interpreting our empirical results through the lens of our model. Specifically, we explore the sensitivity of our results with respect to a long-run annual debt-to-output level ($\mu_B/4$) of 30%. We view this exercise as a comparison of economies with different fiscal regimes due to different tolerance for long-run public debt. Equivalently, we can see this counterfactual exercise as a way to assess the economic significance of the link between public debt and growth.

When we consider the calibration in which average debt is 30% of output, the unconditional average of *HML-R&D* decreases by 20%, i.e., 65 annual basis points. Not surprisingly, with a lower cost of capital for R&D-intensive firms, there is more investment in innovation and the growth rate of GDP increases by 23 basis points, i.e., 12% in relative terms. In other words, higher steady state debt comes with a relatively higher cost of capital for innovative

firms and lower growth.

In the next section, we show that our results on the link between expected *HML-R&D* returns, growth, and different levels of steady-state government debt carry over to the time-series, that is, persistent increases in $DGDP$ depress future expected growth, much as our empirical results suggest.

4.2.1 Debt and Innovation Returns

We now examine the evidence linking $DGDP$, expected returns to innovative firms and growth, uncovered in our initial empirical analysis, through the lens of our model. We start by verifying that our model gives rise to similar time series patterns and then proceed to inspect the underlying model mechanism, along with further empirical tests.

Quantifying Predictability. Table 8 reports the results of predictive regressions of (i) future GDP growth rates (panel A) and (ii) future stock returns (panel B) at various horizons on the current debt-to-GDP ratio. Consistent with our time-series evidence, rises in $DGDP$ forecast a slowdown in future growth accompanied with higher future expected stock returns. This holds both for the aggregate market return as well as the return on *HML-R&D*, so that the average cost of capital rises, and especially so for innovative firms. Our model therefore produces endogenous predictability. Even though the extent of predictability is not identical to that in the data, we consider our results significant, as (i) they are obtained without assuming any exogenous time-varying volatility process, and (ii) they are not too far from their empirical counterparts.

In unreported results, we point out that absent fiscal policy shocks, ϵ_ϕ, debt-to-output has half of the volatility measured in our baseline model and accordingly, removing these shocks weakens the quantitative predictability results.

In general, our predictable risk premia could result from either endogenous time-varying conditional volatility of the stochastic discount factor, or time-varying exposure of returns, or

Table 8: Predictive Regressions–Debt/GDP

Horizon J		1	2	4	8	20
		Panel A: $\Delta GDP_{t\to t+J} = d_0^J + d_1^J \cdot DGDP_t + w_{t+J}$				
Data	d_1^J	-0.003	-0.007	-0.015^{*}	-0.032^{**}	-0.101^{***}
		(0.003)	(0.005)	(0.009)	(0.014)	(0.032)
	R^2	0.006	0.009	0.014	0.023	0.070
Model	d_1^J	-0.017	-0.033	-0.065	-0.124	-0.279
	R^2	0.047	0.074	0.102	0.121	0.126
		Panel B: $R_{t\to t+J} = \beta_0 + \beta_{DGDP}^J DGDP_t + \epsilon_{t+J}$				
		HML-R&D				
Data	β_{DGDP}^J	0.10^{**}	0.10^{**}	0.16^{***}	0.26^{***}	0.65^{***}
		(0.04)	(0.04)	(0.04)	(0.05)	(0.13)
	R^2	0.01	0.02	0.03	0.07	0.43
Model	β_{DGDP}^J	0.13	0.18	0.24	0.30	0.37
	R^2	0.02	0.03	0.06	0.09	0.14
		Market				
Data	β_{DGDP}^J	0.13^{***}	0.18^{***}	0.27^{***}	0.33^{***}	0.32
		(0.04)	(0.04)	(0.04)	(0.05)	(0.22)
	R^2	0.02	0.05	0.13	0.19	0.35
Model	β_{DGDP}^J	0.06	0.08	0.11	0.15	0.20
	R^2	0.01	0.01	0.01	0.02	0.04

Notes: Our quarterly data sample is from the period 1975:Q1–2013:Q4. In panel B, all variables are standardized by their respective standard deviations. *HML-R&D* is measured using equally-weighted returns from portfolios sorted on R&D-to-Assets. We adopt the Stambaugh (1999) OLS bias correction method for β_{DGDP}^J in panel B. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

a combination of the two. Figure 3 sheds light on the mechanism at work in the model. The leftmost panel verifies that expected excess returns on stock portfolios conditional on $DGDP$ indeed are increasing, as is the spread between high and low R&D portfolios. Moreover, conditional risk premia are approximately linear in $DGDP$, which implies that the overall sensitivity of the cost of capital of different firms to $DGDP$, namely $\partial E_t(R_{i,t+1}^{ex})/\partial DGDP_t$, is roughly constant.

Intriguingly, as the rightmost panel of figure 3 shows, the movements in conditional expected returns are only marginally affected by changes in the conditional volatility of the SDF, as this conditional volatility is roughly flat across $DGDP$ levels. This suggests that

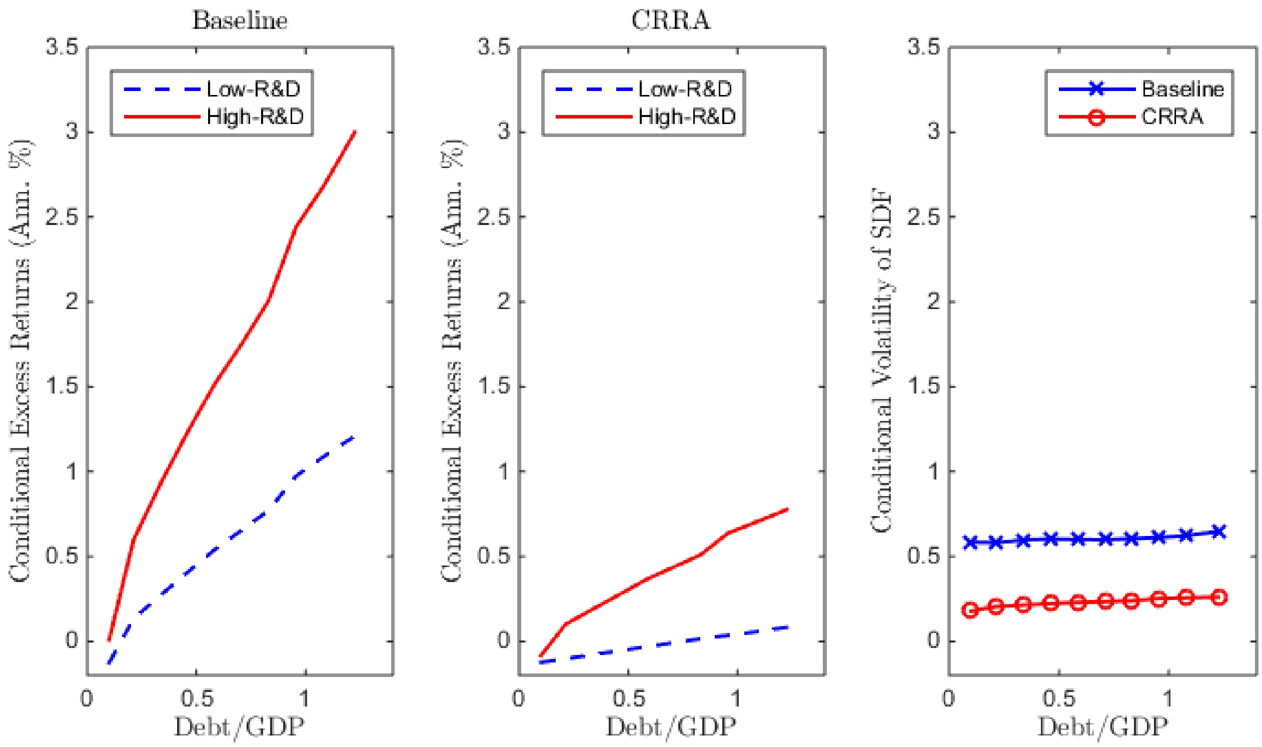

Fig. 3: Conditional Risk Premia (annualized, %)

Notes – This figure shows the unlevered conditional excess returns of the *Low-R&D* and *High-R&D* from a long simulation of the model. Conditional excess returns are sorted into deciles based on their corresponding $DGDP$ and plotted. All parameters are calibrated as in table 6.

our predictability results are driven by time-varying exposure of returns to $DGDP$.

A Conditional Three-factor Model Representation. The lack of significant heteroskedasticity in the SDF, documented in figure 3, suggests that the reduced form of our model corresponds to a conditional three-factor model with nearly constant market prices of risk and time-varying betas. Excess returns in our model can therefore be approximated by

the following reduced-form system of equations

$$E_t[R^{ex}_{i,t+1}] = \sum_{j=1}^{J} \beta^i_{j,t}\lambda_j \tag{25}$$
$$R^{ex}_{i,t+1} = a^i + \sum_{j=1}^{J} \beta^i_{j,t} Factor_{j,t+1} + \epsilon^i_{t+1}$$
$$\beta^i_{j,t} \approx \beta^{0i}_j + \beta^{1i}_j DGDP_t,$$

where our J factors refer to government financing shocks, government spending-to-output shocks, and productivity shocks. We let $\lambda_j, j \in \{1, 2, 3\}$ denote the implied market prices of risk for our exogenous shocks.

Consistent with the model, the exposures of the returns to the underlying factors, $\beta^i_{j,t}$, are allowed to be time-varying. Clearly, conditional betas in the model are affected by $DGDP$, as well as by productivity and government expenditures-to-output ratio. Quantitatively, the last two exogenous state variables play a negligible role once we use $DGDP$. Hence we abstract away from them for the sake of parsimony and without loss of generality. The linearity of the conditional risk premia with respect to $DGDP$ depicted in the left panel of figure 3 suggests that conditional betas are affine in $DGDP$.

According to the empirical model detailed in the system of equations (25), the overall sensitivity of the cost of capital for stock i with respect to movements in $DGDP$,

$$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t = \sum_{j=1}^{J} \beta^{1i}_j \lambda_j, \tag{26}$$

is a composite of both the extent of time-variation of the betas, β^{1i}_j, and the market price of risk associated with our factors, λ_j. The impulse responses of the SDF to negative realizations of our fundamental shocks give us guidance on the model-implied sign of our three market prices of risk. Figure 4 shows the results. Consistent with intuition, the model predicts a positive price of risk for productivity, and negative ones for government expenditure and

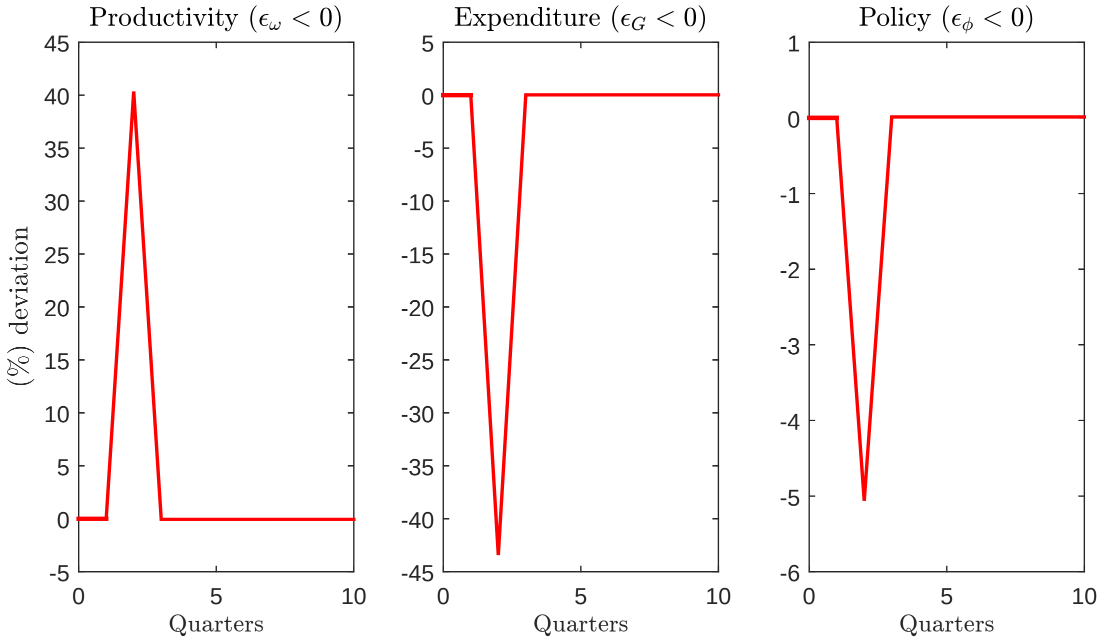

Fig. 4: SDF Impulse Responses to Fundamental Shocks

Notes – This figure shows the impulse response of the stochastic discount factor (SDF) in our DSGE model with respect to negative shocks. Responses are in quarterly percentages. All parameters are calibrated as in table 6.

fiscal policy shocks. Indeed, a sudden reduction in $DGDP$ is a good state for households.

In this setting, movements in expected returns on *HML-R&D* have to be driven by differential sensitivity of the respective betas to $DGDP$. Specifically, it must be the case that

$$\frac{\partial E_t(R^{ex}_{rd,t+1})}{\partial DGDP_t} - \frac{\partial E_t(R^{ex}_{t+1})}{\partial DGDP_t} > 0,$$

so that a higher debt-to-output ratio increases the spread in the expected returns on intangible and tangible capital, in line with the leftmost panel of figure 3.

Under our data-driven calibration, policy shocks, $\epsilon_{\phi,t}$, emerge as a critical driver of the conditional exposure coefficients. Intuitively, our way to model political uncertainty in the government budget process allows for sizeable variation in the debt-to-output ratio independent from productivity and expenditure shocks. In what follows, we document that fiscal policy shocks give rise to endogenous tax uncertainty, to which tangible and intangible assets exhibit differential exposure because of a reallocation motive.

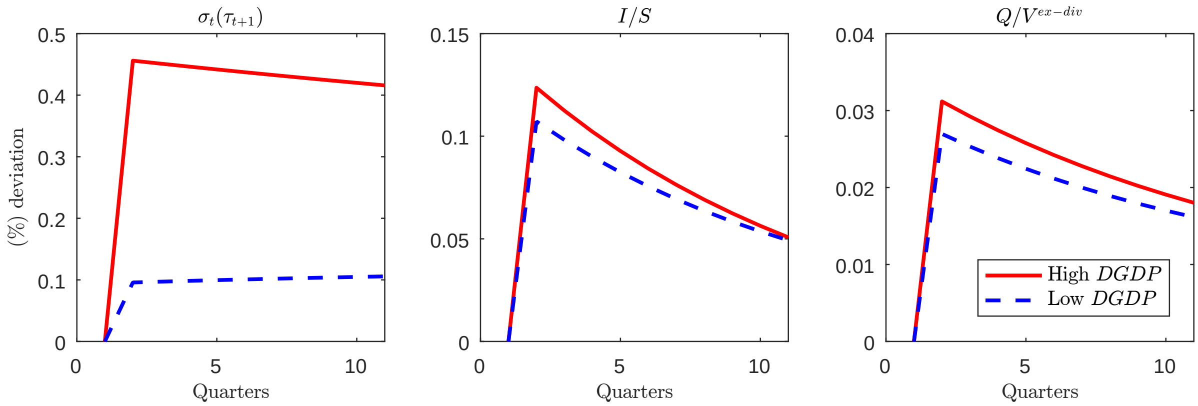

Fig. 5: Conditional Tax Risk, Investment Reallocation and Asset Prices

Notes – This figure shows the conditional average impulse responses to a positive one-standard-deviation shock to $\epsilon_{\phi,t}$. $\sigma_t(\tau_{t+1})$ is the conditional volatility of the tax rate, I/S is the ratio of tangible capital investment to R&D investment, and Q/V^{ex-div} is the ex-dividend price ratio of tangible to intangible capital. The impulse responses are conditional with respect to the model being in 'High $DGDP$' states and 'Low $DGDP$' states. We define 'High $DGDP$' states as the top 5% of $DGDP$ values from a simulated stationary distribution from the model after a burn-in of 100 periods. Equivalently, we define 'Low $DGDP$' states as the bottom 5% of $DGDP$ values from the same stationary distribution. The model is then shocked from the respective states (conditional on $DGDP$), and impulse responess are averaged over the respective $DGDP$ bins. All parameters are calibrated as in table 6.

Endogenous Time-Varying Tax Uncertainty. In figure 5, we depict the response of variables of interest with respect to a positive debt policy shock, $\epsilon_\phi > 0$. This shock is useful to understand the mechanism behind our model because it is a pure public financing shock that affects neither government expenditures nor R&D productivity. In the first panel on the left, we show two important features of the tax rate implied by the government's budget constraint in equilibrium. First, expansionary fiscal shocks increase tax rate uncertainty, as measured by the conditional volatility of the tax rate going forward. Second, this response is more pronounced when the debt-to-output ratio in the economy is above average.

Before proceeding, we confirm and gauge the magnitude of this effect in the data. Specifically, both in the model and in the data we estimate the volatility of the tax rate, σ_t^τ, from

the following system of equations:

$$\tau_t = \mu_t^\tau + \sigma_t^\tau \epsilon_t^\tau$$
$$\mu_t^\tau = \mu^\tau + \rho^\tau \mu_{t-1}^\tau$$
$$(\sigma_t^\tau)^2 = \omega + \alpha^\tau (\sigma_{t-1}^\tau)^2 + \beta^\tau (\epsilon_{t-1}^\tau)^2.$$

In the data, we obtain the following results:

$$(\sigma_t^\tau)^2 - \overline{\sigma^\tau}^2 = \underset{(0.002)}{0.006} \cdot DGDP_{t-1} + \epsilon_{\sigma,\tau},$$

which are almost exactly replicated by simulated data:

$$(\sigma_t^\tau)^2 - \overline{\sigma^\tau}^2 = 0.005 \cdot DGDP_{t-1} + \epsilon_{\sigma,\tau}.$$

Thus, both in the data and in the model, rises of the debt-to-GDP ratio come with higher tax uncertainty going forward. Further, the data support the notion that policy shocks are a relevant driver of the time variation of tax volatility. More precisely, we find that in the data, fiscal policy shocks drive fiscal uncertainty going forward in that :

$$(\sigma_t^\tau)^2 = \underset{(0.000)}{0.001} + \underset{(0.025)}{0.095} \cdot (\sigma_{t-1}^\tau)^2 + \underset{(0.003)}{0.006} \cdot \widehat{\epsilon_{t-1}^{DGDP}} + \epsilon_{\sigma,\tau},$$

where $\widehat{\epsilon_{t-1}^{DGDP}}$ is the fitted residuals from the regression

$$DGDP_t = a_0 + a_1 DGDP_{t-1} + a_2 \cdot gy_t + a_3 TFP_t + \epsilon_t^{DGDP},$$

used to calibrate the model. Hence, as in Croce, Nguyen, and Schmid (2012), fiscal uncertainty is an endogenously time-varying determinant of risk which becomes more relevant as the debt-to-output ratio increases.[10] Given this observation, the results depicted in the

[10] In appendix B, we reproduce the Croce, Nguyen, and Schmid (2012) intuition for this result through

left panel of figure 3 should not appear surprising: as the debt-to-output ratio increases, uncertainty increases as well, and all capital stocks must pay a higher expected return.

Endogenous Time-Varying Reallocation. The novel insight of our model points to the existence of an important reallocation channel, consistent with that documented empirically in table 4. As already noted previously in the literature (see, for example, Bocola and Gornemann 2013 and Bianchi and Kung 2014), the present value of monopoly rents is very sensitive to fundamental shocks. Consistent with the data (as documented, for example, by Elsaify (2015)), in our model, R&D intensive firms charge higher markups. As a result, the innovation sector is more sensitive to debt policy shocks and is subject to more severe fluctuations in investment. Equivalently, upon the arrival of an expansionary public debt shock, the household cuts down total investment but simultaneously increases its share of investment in the tangible capital stock (figure 5, middle panel). As a result, this reallocation aggravates the capital loss for the R&D sector, whereas it works as a valuable hedge for firms that are tangible-capital intensive (figure 5, rightmost panel).

Since this reallocation effect is more pronounced when the debt-to-output ratio is higher, the hedging motive manifests itself as a more sizable spread across the exposure coefficients of our two stocks exactly when debt is greater. Consistent with this intuition, the difference in the conditional risk premia of the two capital stocks increases in $DGDP$, as shown in the left panel of figure 3.[11]

4.2.2 Sensitivity

CRRA. To quantify the role played by preferences, we solve our model under a configuration with CRRA preferences by setting $\gamma = 1/\psi = 10$. This calibration confirms a positive

a simple example that enables us to have closed-form solutions. Intuitively, in production economies with random productivity, future tax rates are uncertain because the government faces uncertainty on the future tax base. When debt-to-output is high, tax-base uncertainty turns into more pronounced tax rate volatility.

[11] A small part of this increase is also due to the larger volatility of the stochastic discount factor (SDF) (figure 3, rightmost panel). The discount rate channel is expected in general equilibrium, as consumption inherits the time-varying volatility of the tax rate. Quantitatively, however, this channel is negligible in our model.

link between expected returns and the debt-to-output ratio, and it also predicts that intangible capital should be more sensitive to the size of government debt than tangible capital. From a quantitative point of view, this specification of the model is unsatisfactory. As shown in the middle panel of figure 3, the implied spread in the expected excess returns across tangible and intangible capital is modest and further from the data.

No Government Risks. To quantify the role of fiscal shocks, we solve our model under a calibration that differs from that reported in table 6 because we impose $A_\phi = \sigma_G = 0$. Under this configuration, TFP shocks are active whereas all other exogenous fiscal risks are muted. We find that $E_t[HML - R\&D]$ declines to 1.45%, implying that in the model about 65% of the total *HML-R&D* premium is driven by fiscal shocks. Not surprisingly, the unconditional growth rate increases as well, by about 8 basis points per year.

Furthermore, $\frac{\partial E_t(R^{rd}_{t+1} - R_{t+1})}{\partial DGDP_t}$ becomes nearly null, meaning that the model fails to produce predictability. This result is consistent with our previous observation: since our exogenous R&D productivity process does not produce any relevant reallocation motive, the conditional exposures of our returns are constant with respect to productivity.

5 Cross-Sectional Asset Pricing Tests

In this section, we provide novel empirical evidence supporting the cross-sectional asset pricing implications of our model documented in the previous section. These tests are important as they provide direct support for our risk-based mechanism underlying the links between government debt and growth.

Conditional model with time-varying betas. We estimate the pricing model detailed in the system of equations (25) in the data using our three empirical macroeconomic factors, namely, the log difference of government spending-to-output (ΔGY), utilization-adjusted productivity (ΔTFP), and debt-to-GDP ratio ($\Delta DGDP$). We choose changes in DGDP as

empirical proxy for fiscal shocks to confirm that our results are broad and do not depend on a specific choice of the fiscal policy rule. Untabulated results confirm that our main findings continue to hold when we work with our filtered policy shocks, $\widehat{\epsilon_t^{DGDP}}$, as opposed to $\Delta DGDP$.

We expand our cross section of test assets to keep our inference sharp. Specifically, in addition to the market and our cross section of R&D-intensity sorted portfolios, we consider the 25 portfolios constructed by Fama and French (FF25) using size and book-to-market, and the entire market. We also add SMB and HML to study the link between $DGDP$, size, and book-to-market. We use GMM to estimate all coefficients simultaneously and report our main results in table 9.[12]

We are interested in assessing the sensitivity of the cost of capital of different firms to movements in $DGDP$, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$, as specified in the model in (26). We report our estimates in the top portion of table 9 together with standard errors computed using the delta method. The estimates of the market price of risk are in the middle of the table, followed by the results for the J-test associated with our GMM.

We have four observations. First of all, this cross-sectional estimation both confirms and sharpens the results obtained through our predictability regressions. The variations that we obtain for the market and *HML-R&D* are very similar to those obtained in table 2 over a 1-quarter horizon. Furthermore, the adverse effect of public debt on the cost of capital is a very pervasive phenomenon as it is also present in the extreme FF25 portfolios.

Intriguingly, SMB and HML exhibit no significant sensitivity to DGDP. The relevance of this outcome is twofold, as it suggests that (i) our results are not a mere restatement of size or book-to-market effects, and (ii) our strategy of sorting firms according to their R&D intensity is essential for the correct assessment of the impact of public debt on the cross section of equity returns.

Second, these results hold regardless of whether we use equally-weighted or value-weighted

[12] In an extension, we also expand the set of test assets to financial constraints adjusted returns. We recover the results from our baseline estimates. We report these in table A13. in the appendix.

returns for our R&D-sorted portfolios. We also conduct our estimation using a different measure of R&D intensity to form our cross-section. Specifically, we sort firms according to their expenditures in R&D relative to capital expenditure, as in Lin (2012), and obtain very similar results (see table A11). We find it reassuring that our results are robust to different ways of measuring innovation intensity across firms. In the appendix, we show that our results also hold when we focus only on positive-R&D firms (see table A12).

Third, the estimated signs of the market prices of risk of our three factors are consistent with the predictions of our DSGE model about the responses of the SDF to our fundamental shocks depicted in figure 4. Specifically, the SDF implied by the system of equations (25) can be written as $m_t = \overline{m} - bF_t$, in which $b = -E(FF')^{-1}\lambda$, F comprises our three macroeconomic risk factors, and λ is the vector of the market prices of risk.

In our data, the implied SDF loadings have opposite sign with respect to our estimated market prices of risk. As a result, both in the model and in the data, states with low productivity are associated to high marginal utility. This is a very common result in production economies. In contrast, government expenditure has a positive loading in the SDF. In our model, this is true because government expenditure is wasteful. According to our estimates, shocks that produce lower levels of debt-to-output should decrease marginal utility. This holds in our model as well, as unexpected reductions of debt result in lower future tax uncertainty and represent good news.

Finally, we note that including $DGDP$ in our estimation reduces the mean absolute pricing errors (MAE) by roughly 15% for value-weighted returns and 20% for equally-weighted returns. In both cases, $DGDP$ increases the cross-sectional R^2 by about 50 percent. This observation corroborates the relevance of accounting for $DGDP$ in cross-sectional asset pricing tests.

6 Conclusion

We present novel empirical evidence that government debt, as measured for example by the debt-to-output ratio, is a determinant of risk in stock markets. In the time series, the debt-to-output ratio significantly predicts higher future aggregate stock returns at longer horizons, even when we control for standard predictors such as price-dividend ratios and market volatility.

The sensitivity of expected returns to debt-to-output is higher for R&D intensive firms, implying that their cost of equity increases more when public debt grows. Simultaneously, we find that high levels of debt-to-output forecast both lower tangible and intangible investment, as well as lower output growth over the medium term.

We interpret our empirical results in the context of an equilibrium production economy in which endogenous innovation drives long-term growth. Corporate investment and innovation depend on the fiscal policy stance of the government, which resorts to taxation to ensure a balanced budget in the long run. Unexpected movements in the government's debt policy give rise to endogenous time-varying exposure to macroeconomic shocks priced in the cross-section of returns.

We find that agents require a premium increasing in debt-to-output in order to hold innovative stocks as compensation for this time-varying exposure. We test this hypothesis in the cross-section of equity returns and fail to reject it. High levels of public debt are then associated with slowdowns in innovation and growth. Both the model and our empirical investigation thus highlight the role of political and fiscal uncertainty in shaping future aggregate growth. Future work should asses this link accounting for productive government expenditures, in the spirit of Belo and Yu (2013).

Table 9: Conditional Macro Factors Model

	EW	VW
	$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$	
Low–R&D	0.04	0.03
	(0.04)	(0.03)
High–R&D	0.11***	0.10**
	(0.03)	(0.04)
HML–R&D	0.08***	0.07**
	(0.01)	(0.03)
Market	0.16***	0.14***
	(0.04)	(0.04)
Small–Low B/M	0.17***	0.14***
	(0.04)	(0.05)
Small–High B/M	0.16***	0.12**
	(0.04)	(0.05)
Big–Low B/M	0.18***	0.18***
	(0.04)	(0.05)
Big–High B/M	0.13***	0.09**
	(0.03)	(0.04)
SMB	0.00	−0.02
	(0.02)	(0.03)
HML	−0.03	−0.08**
	(0.03)	(0.04)
J-Test	5.96	5.96
p-value	1.00	1.00
Annual MAE	2.41	2.03
Annual MAE (excl. $\Delta DGDP$)	2.92	2.30
Cross sectional R^2	0.47	0.57
Cross sectional R^2 (excl. $\Delta DGDP$)	0.30	0.37

	EW			VW		
	$\Delta DGDP$	ΔTFP	ΔGY	$\Delta DGDP$	ΔTFP	ΔGY
Price of risk, λ	−0.009***	0.008***	−0.018***	−0.015***	0.007***	−0.026***
	(0.003)	(0.001)	(0.003)	(0.003)	(0.002)	(0.004)

Notes: This table shows results from our GMM estimation of the conditional macro factor model detailed in the system of equations (25). Our macro factors consist of changes to debt-to-output ratio ($\Delta DGDP$), government spending-to-output (ΔGY), and TFP (ΔTFP). In the top portion of the table, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t = \sum_{j=1}^{J} \beta_j^{1i}\lambda_j$, where λ_j denotes the market price of risk for factor j. EW (VW) denotes equally-weighted (value-weighted) returns. The set of test assets includes: our bottom-10 (Low-R&D) and top-10 (High-R&D) portfolios; our 'Middle' portfolio; a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*); the Fama-French 25 size/book-market-sorted portfolios; the Fama-French SMB and HML factors; and the full market portfolio. Newey-West (1987) standard errors are in parentheses. Data are from 1975:Q1 to 2013:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Our J-Test is based on 29 degrees of freedom.

References

Bai, Hang, 2016, Predictable returns over the credit cycle, *UConn Working paper*.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, 2016, Measuring Economic Policy Uncertainty, *The Quarterly Journal of Economics* 131, 1593–1636.

Barro, Robert J., and Charles J. Redlick, 2011, Macroeconomic Effects From Government Purchases and Taxes, *The Quarterly Journal of Economics* 126, 51–102.

Belo, Frederico, Santiago Bazdresch, and Xiaoji Lin, 2011, Labor Hiring, Investment and Stock Return Predictability in the Cross Section, *Journal of Political Economy* forthcoming.

Belo, Frederico, Vito D. Gala, and Jun Li, 2013, Government spending, political cycles, and the cross section of stock returns, *Journal of Financial Economics* 107, 305–324.

Belo, Frederico, and Jianfeng Yu, 2013, Government investment and the stock market, *Journal of Monetary Economics* 60, 325–339.

Bi, Huixin, and Eric Leeper, 2010, Sovereign Debt Risk Premia and Fiscal Policy in Sweden, Indiana University Working Paper.

Bianchi, Francesco, and Howard Kung, 2014, Growth, Slowdowns, and Recoveries, Working Paper 20725 National Bureau of Economic Research.

Bloom, Nicholas, 2009, The Impact of Uncertainty Shocks, *Econometrica* 77, 623–685.

Bocola, Luigi, and Nils Gornemann, 2013, Risk, Economic Growth and the Value of U.S. Corporations, Working paper.

Bohn, Henning, 1998, The Behavior of U. S. Public Debt and Deficits, *The Quarterly Journal of Economics* 113, 949–963.

Campanale, Claudio, Rui Castro, and Gian Luca Clementi, 2010, Asset pricing in a production economy with Chew–Dekel preferences, *Review of Economic Dynamics* 13, 379–402.

Campbell, John Y., and Robert J. Shiller, 1988, The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors, *Review of Financial Studies* 1, 195–228.

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001, The Stock Market Valuation of Research and Development Expenditures, *The Journal of Finance* 56, 2431–2456.

Cochrane, John H., 1996, A Cross-Sectional Test of an Investment-Based Asset Pricing Model, *Journal of Political Economy* 104, 572–621.

Cochrane, John H., 2008, The Dog That Did Not Bark: A Defense of Return Predictability, *Review of Financial Studies* 21, 1533–1575.

Comin, Diego, and Mark Gertler, 2006, Medium Term Business Cycles, *American Economic Review* 96, 523–551.

Comin, Diego A, Mark Gertler, and Ana Maria Santacreu, 2009, Technology innovation and diffusion as sources of output and asset price fluctuations, Harvard Business School Working Paper.

Corhay, Alexandre, Howard Kung, and Lukas Schmid, 2015, Competition, Markups and Predictable Returns, Working Paper, Duke University.

Croce, Max, Howard Kung, Thien T. Nguyen, and Lukas Schmid, 2012, Fiscal Policies and Asset Prices, *Review of Financial Studies.*

Croce, Max, Thien T. Nguyen, and Lukas Schmid, 2012, The Market Price of Fiscal Uncertainty, *Journal of Monetary Economics* 2011 Carnagie-Rochester-NYU Conference on Public Policy.

Demirci, Irem, Jennifer Huang, and Clemens Sialm, 2016, Government Debt and Capital Structure Decisions: International Evidence, University of Texas Austin Working Paper.

Dixit, Avinash K, and Joseph E Stiglitz, 1977, Monopolistic competition and optimum product diversity, *The American Economic Review* 67, 297–308.

Easterly, William, and Sergio Rebelo, 1993, Fiscal Policy and Economic Growth: An Empirical Investigation, *Journal of Monetary Economics* 32, 417–458.

Elsaify, Amora, 2015, The Innovation Premium, Working Paper, University of Pennsylvania.

Fama, Eugene, and Kenneth R. French, 1992, The Cross Section of Expected Stock Returns, *The Journal of Finance* XLVII, 427–465.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Favero, Carlo, and Tommaso Monacelli, 2005, Fiscal Policy Rules and Regime (In)Stability: Evidence from the U.S., Bocconi University Working Paper.

Fernald, John, et al., 2012, A quarterly, utilization-adjusted series on total factor productivity, *Federal Reserve Bank of San Francisco Working Paper.*

Gavazzoni, Federico, and Ana Maria Santacreu, 2015, International R&D Spillovers and Asset Prices, Working Paper, INSEAD.

Glover, Brent, F. Gomes, and Amir Yaron, 2010, Corporate Taxes, Leverage, and Business Cycles, Working paper, Wharton School.

Gomes, Francisco, Alex Michaelides, and Valery Polkovnichenko, 2010, Quantifying the Distortionary Fiscal Cost of "The Bailout", Working Paper, London Business School.

Gomes, Francisco, Alex Michaelides, and Valery Polkovnichenko, 2012, Fiscal Policy in an Incomplete Markets Economy, Review of Financial Studies, forthcoming.

Gomes, Francisco J., Laurence J. Kotlikoff, and Luis M. Viceira, 2011, The Excess Burden of Government Indecision, *NBER: Tax Policy and the Economy, Volume 26.*

Gourio, Francois, 2012, Disaster Risk and Business Cycles, *The American Economic Review* 102, 2734–2766.

Gourio, Francois, 2013, Credit Risk and Disaster Risk, *American Economic Journal: Macroeconomics* 5, 1–34.

Graham, John, Mark T. Leary, and Michael R. Roberts, 2014, How Does Government Borrowing Affect Corporate Financing and Investment?, Working Paper 20581 National Bureau of Economic Research.

Grossman, Gene M, and Elhanan Helpman, 1991, Quality ladders in the theory of growth, *The Review of Economic Studies* 58, 43–61.

Hadlock, Charles J, and Joshua R Pierce, 2010, New evidence on measuring financial constraints: Moving beyond the KZ index, *Review of Financial studies* 23, 1909–1940.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015a, A Comparison of New Factor Models, Working paper, The Ohio State University.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015b, Digesting Anomalies: An Investment Approach, *Review of Financial Studies* 28, 650–705.

Jaimovich, Nir, and Sergio Rebelo, 2017, Non-linear Effects of Taxation on Growth, *Journal of Political Economy* 125(1), 265–291.

Jermann, Urban Joseph, 1998, Asset Pricing in Production Economies, *Journal of Monetary Economics* 41, 257–275.

Kaltenbrunner, Georg, and Lars A. Lochstoer, 2010, Long-Run Risk through Consumption Smoothing, *Review of Financial Studies* 23, 3190–3224.

Kaplan, Steven N, and Luigi Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints?, *The Quarterly Journal of Economics* 112, 169–215.

Kelly, Bryan, Lubos Pastor, and Pietro Veronesi, 2015, The Price of Political Uncertainty: Theory and Evidence from the Option Market, *Journal of Finance (Forthcoming).*

Koijen, Ralph S.J., Hanno Lustig, and Stijn Van Nieuwerburgh, 2010, The Cross-Section and Time-Series of Stock and Bond Returns, Working Paper 15688 NBER.

Kuehn, Lars Alexander, 2008, Asset Pricing and Real Investment Commitment, Working Paper, CMU.

Kuehn, Lars Alexander, 2009, Disentangling Investment Returns and Stock Returns: The Importance of Time-to-Build, Working Paper, CMU.

Kung, Howard, and Lukas Schmid, 2015, Innovation, Growth, and Asset Prices, *The Journal of Finance* 70, 1001–1037.

Leeper, Eric M., Michael Plante, and Nora Traum, 2010, Dynamics of fiscal financing in the United States, *Journal of Econometrics* 156, 304–321.

Lettau, Martin, and Sydney C. Ludvigson, 2005, Expected returns and expected dividend growth, *Journal of Financial Economics* 76, 583–626.

Li, Dongmei, 2011, Financial constraints, R&D investment, and stock returns, *Review of Financial Studies* 24, 2974–3007.

Lin, Xiaoji, 2012, Endogenous technological progress and the cross-section of stock returns, *Journal of Financial Economics* 103, 411–427.

Liu, Yang, 2016, Government Debt and Expected Stock Returns, Wharton Working Paper.

Lustig, Hanno, Antje Berndt, and Sevin Yeltekin, 2012, How Does the U.S. Government Finance Fiscal Shocks?, *American Economic Journal: Macroeconomics* 4, 69–104.

Lustig, Hanno, Christopher Sleet, and Sevin Yeltekin, 2008, Fiscal Hedging with Nominal Assets, *Journal of Monetary Economics* 32, 710–727.

Manela, Asaf, and Alan Moreira, 2016, News implied volatility and disaster concerns, *Journal of Financial Economics* Forthcoming.

McGrattan, Ellen R., and Edward C. Prescott, 2005, Taxes, Regulations, and the Value of U.S. and U.K. Corporations, *Review of Economic Studies* 72, 767–796.

Mehra, Rajnish, and Edward C. Prescott, 1985, The Equity Premium: A Puzzle, *Journal of Monetary Economics* 15, 145–161.

Mendoza, Enrique, Gian Maria Milesi-Ferretti, and Patrick Asea, 1997, On the Ineffectiveness of Tax Policy in Altering Long-Run Growth: Harberger's Superneutrality Conjecture, *Journal of Public Economics* 66, 99–126.

Mendoza, Enrique, and Linda Tesar, 1998, The International Ramifications of Tax Reforms; Supply-Side Economics in a Global Economy, *American Economic Review* 88, 226–245.

Newey, Whitney K., and Kenneth D. West, 1987, A Simple, Positive Semi-Definite, Heteroskedasticity And Autocorrelation Consistent Covariance Matrix, *Econometrica* 55.

Pastor, Lubos, and Robert F. Stambaugh, 2003, Liquidity Risk and Expected Stock Returns, *Journal of Political Economy* 111, 642–685.

Pastor, Lubos, and Pietro Veronesi, 2012, Uncertainty about Government Policy and Stock Prices, *Journal of Finance* 64, 1219–1264.

Pastor, Lubos, and Pietro Veronesi, 2013, Political Uncertainty and Risk Premia, *Journal of Financial Economics* Forthcoming.

Romer, Paul M, 1990, Endogenous Technological Change, *Journal of Political Economy* 98, 71–102.

Schmitt-Grohe, Stephanie, and Martin Uribe, 2007, Optimal, Simple, and Implementable Monetary and Fiscal Rules, *Journal of Monetary Economics* 54, 1702–1725.

Sialm, Clemens, 2006, Stochastic Taxation and Asset Pricing in Dynamic General Equilibrium, *Journal of Economic Dynamics and Control* 30.

Sialm, Clemens, 2009, Tax Changes and Asset Pricing, *American Economic Review* 99(4).

Stambaugh, Robert F, 1999, Predictive regressions, *Journal of Financial Economics* 54, 375–421.

Tallarini, Thomas D., 2000, Risk Sensitive Real Business Cycles, *Journal of Monetary Economics* 45, 507–532.

Titman, Sheridan, KC John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of financial and Quantitative Analysis* 39, 677–700.

Welch, Ivo, and Amit Goyal, 2008, A comprehensive look at the empirical performance of equity premium prediction, *Review of Financial Studies* 21, 1455–1508.

A Additional Statistics and Tests

In table A1, we provide the most frequent industries in both our high and low R&D-intensity sorted portfolios.

Table A1: Top 10 Industries in R&D Intensity Sorted Portfolio

Panel A: All Firms

Low-R&D		High-R&D	
Category	% Count	Category	% Count
Eating Places	9.9	Prepackaged Software	12.9
Crude Petroleum and Natural Gs	3.6	Pharmaceutical Preparations	11.5
Grocery Stores	3.5	Biological Pds, Ex Diagnstics	10.2
Misc Amusement and Rec Service	3.0	Semiconductor,Related Device	6.8
Variety Stores	2.6	Electromedical Apparatus	3.7
Hotels and Motels	2.5	In Vitro,In Vivo Diagnostics	3.4
Women's Clothing Stores	2.5	Cmp Integrated Sys Design	3.3
Real Estate Investment Trust	2.2	Computer Communications Equip	3.3
Department Stores	2.0	Radio, TV Broadcast, Comm Eq	3.0
Computers and Software-Whsl	1.8	Tele and Telegraph Apparatus	2.9
Total	33.4	Total	61.2

Panel B: Positive R&D Firms

Low-R&D		High-R&D	
Category	% Count	Category	% Count
Petroleum Refining	5.4	Prepackaged Software	12.8
Crude Petroleum and Natural Gs	3.3	Pharmaceutical Preparations	11.6
Steel Works and Blast Furnaces	3.1	Biological Pds, Ex Diagnstics	10.4
Phone Comm Ex Radiotelephone	2.8	Semiconductor,Related Device	6.7
Mng, Quarry Nonmtl Minerals	1.8	Electromedical Apparatus	3.7
Metal Mining	1.8	In Vitro,In Vivo Diagnostics	3.5
Indl Inorganic Chemicals	1.6	Computer Communications Equip	3.3
Radiotelephone Communication	1.4	Cmp Integrated Sys Design	3.3
Paper Mills	1.3	Radio, TV Broadcast, Comm Eq	3.0
Paperboard Mills	1.2	Tele and Telegraph Apparatus	2.9
Total	23.7	Total	61.3

Notes: This table shows the top-10 industries in our baseline high and low R&D-sorted portfolios. We count SIC codes across time and firms in each portfolio and report the most frequent industries within each portfolio. In Panel A, we include all firm. In Panel B, we only consider firms with positive R&D expense.

In table A2, we provide predictability regressions based on five portfolios sorted on R&D intensity. Each portfolio comprises an equal number of firms.

Table A2: $DGDP$ **and Predictability of Returns to Innovation (II)**

Horizon (J)	1	2	4	8	20
HML-R&D (EW)	0.06	0.11	0.26**	0.61***	2.61***
	(0.05)	(0.09)	(0.11)	(0.16)	(0.70)
R^2	0.02	0.03	0.04	0.09	0.48
HML-R&D (VW)	0.14***	0.29***	0.59***	1.21***	2.91**
	(0.05)	(0.08)	(0.09)	(0.15)	(1.16)
R^2	0.06	0.09	0.14	0.25	0.33

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return and $DGDP$ is the debt-to-output ratio. We report results for the portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*), where returns are either equally-weighted (EW) or value-weighted (VW). The underlying portfolios are constructed by sorting firms based on innovation intensity into five portfolios, each with an equal number of firms. Innovation intensity is measured as the ratio of R&D expenses to total assets. Our quarterly sample is 1975:Q1–2013:Q4. Estimated coefficients have been adjusted with the Stambaugh bias correction. Bootstrap standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

In table A3, we report basic statistics on a restricted sample, in which we consider only firms with positive R&D expenditures.

Table A3: Data Summary Statistics – Positive R&D Firms

	Low	Middle	High	*HML-R&D*
	Panel A: Equally-Weighted Portfolio Returns			
Mean	13.97***	16.07***	23.81***	10.39***
	(3.74)	(3.56)	(4.51)	(3.19)
Standard Deviation	25.81	24.57	31.15	22.04
Sample Size	191	191	191	191
	Panel B: Value-Weighted Portfolio Returns			
Mean	5.65**	7.93***	14.86***	9.41***
	(2.87)	(2.66)	(3.67)	(3.08)
Standard Deviation	19.80	18.37	25.33	21.31
Sample Size	191	191	191	191

Notes: This table shows summary statistics for three R&D-sorted portfolios and the implied *HML-R&D* portfolio. We only include firms with positive R&D expense in our cross section. Equally-weighted returns are presented in Panel A and value-weighted returns are presented in Panel B. All returns are presented in annualized percentages. Our quarterly sample starts in 1966:Q2 and ends in 2013:Q4. Standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table A4 shows sensitivity of our baseline estimates with respect to the lag chosen in the Newey-West estimator.

Table A4: Tstat by Newey-West Lags – HML R&D Returns

	Lag (quarters)				
Point estimate	2	4	6	8	24
2.76	5.19	4.29	3.92	3.76	4.09

Notes: This table shows sensitivity results from varying the lags for computing Newey-West (1987) standard errors in our univariate predictive return regressions. The estimate is performed without adjusting for the Stambaugh bias correction (in table 2, the adjusted estimate is 2.31). We report results from the *HML-R&D* equally-weighted returns for the predictive regression at 20 quarters horizon using our baseline portfolios. Data are from 1975:Q1 to 2013:Q4.

Table A5 documents sensitivity of our baseline estimates with respect to additional return predictors. Table A6 presents results from predictive regressions based on characteristic-adjusted returns.

Table A5: Predictive Regression for HML-R&D – Additional Factors

	β^J_{DGDP}	t-stat
First 2 principle components	2.96	2.44
First 3 principle components	2.94	2.39
First 2 principle components plus PD and MV	1.99	2.00
First 3 principle components plus PD and MV	1.99	2.00

Notes: This table shows predictive return regressions using principle components from the panel of regressors used in Welch and Goyal (2008) (WG). We report results for our equally-weighted *R&D-HML* portfolio at a horizon of 20 quarters by estimating $R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta'^J_W WG_t + \epsilon_{t+J}$, where WG_t represents either the first two or three principle components from a panel of the Goyal and Welch regressors. We also control for integrated market returns volatility (MV) and price-dividends (PD) ratio.

Table A6: Predictive Regressions - HML-R&D Adjusted Returns

	Univariate–β_{DGDP}					Multivariate–β_{DGDP}				
Horizon J	1	2	4	8	20	1	2	4	8	20
Asset/Book Equity	0.13	0.15	0.19**	0.27***	0.73***	0.06**	0.12**	0.25**	0.59***	2.97***
	(0.11)	(0.11)	(0.08)	(0.08)	(0.20)	(0.03)	(0.06)	(0.11)	(0.21)	(0.57)
R^2	0.02	0.03	0.04	0.09	0.53	0.03	0.04	0.06	0.12	0.52
Asset/Market Equity	0.10	0.11	0.16**	0.23***	0.70***	0.03	0.08	0.15	0.33*	2.21***
	(0.11)	(0.11)	(0.08)	(0.08)	(0.19)	(0.03)	(0.05)	(0.10)	(0.20)	(0.62)
R^2	0.01	0.02	0.03	0.06	0.48	0.02	0.03	0.03	0.08	0.40
KZ Index	0.13	0.15	0.19**	0.28***	0.75***	0.06*	0.14*	0.29*	0.73**	4.01***
	(0.11)	(0.11)	(0.08)	(0.08)	(0.19)	(0.04)	(0.08)	(0.17)	(0.37)	(0.55)
R^2	0.02	0.03	0.04	0.09	0.55	0.03	0.05	0.08	0.18	0.63
SA Index	0.06	0.06	0.10	0.16**	0.63***	0.02	0.05	0.11	0.32	2.73***
	(0.12)	(0.11)	(0.08)	(0.08)	(0.21)	(0.04)	(0.07)	(0.14)	(0.29)	(0.82)
R^2	0.02	0.03	0.03	0.06	0.39	0.01	0.02	0.02	0.05	0.40

Notes: This table predictive return regressions with characteristic adjusted equal-weighted returns for the HML-R&D portfolio. We separately adjust for asset/book equity, asset/market equity, KZ index, and SA index. The KZ index is constructed following Kaplan and Zingales (1997) and the SA index is constructed following Hadlock and Pierce (2010). We follow the methods in Titman, Wei, and Xie (2004) to form characteristic adjusted returns. Univariate refers to the following regression $R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \epsilon_{t+J}$. In the multivariate regressions, we control for integrated market volatility (MV) and the aggregate price-dividends (PD) ratio.

In tables A7 and A8, we show that even when we restrict our sample to firms with positive R&D expenditures, high levels of government debt forecast higher expected returns for our *HML-R&D* portfolio. In this case, returns are equally-weighted. Tables A9–A10 are based on value-weighted results.

Table A7: $DGDP$ and Predictability of Returns to Innovation (Positive R&D Firms-EW)

Horizon (J)	1	2	4	8	20
			β^J_{DGDP}		
Low-R&D	0.13***	0.23***	0.44***	0.72**	1.26
	(0.04)	(0.08)	(0.16)	(0.35)	(0.94)
R^2	0.07	0.14	0.17	0.18	0.13
High-R&D	0.16***	0.30***	0.57***	1.00**	3.12***
	(0.05)	(0.11)	(0.21)	(0.41)	(1.20)
R^2	0.05	0.10	0.15	0.19	0.33
HML-R&D	0.03	0.07	0.13	0.28	1.86**
	(0.04)	(0.08)	(0.14)	(0.25)	(0.77)
R^2	0.03	0.04	0.07	0.15	0.35
Market	0.11***	0.22***	0.44***	0.87***	1.87***
	(0.02)	(0.05)	(0.10)	(0.21)	(0.52)
R^2	0.05	0.11	0.19	0.33	0.47

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are equal-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. We only include firms with positive R&D expense in our cross-section. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table A8: *PD, MV* and Predictability of Returns to Innovation (Pos. R&D Firms-EW)

Horizon J	1	2	4	8	20
			β^J_{PD}		
Low-R&D	-0.0011^{***}	-0.0021^{***}	-0.0040^{***}	-0.0063^{***}	-0.0077^{*}
	(0.0004)	(0.0007)	(0.0012)	(0.0021)	(0.0046)
High-R&D	-0.0005	-0.0008	-0.0014	-0.0008	-0.0022
	(0.0009)	(0.0016)	(0.0029)	(0.0041)	(0.0043)
HML-R&D	0.0007	0.0013	0.0026	0.0056	0.0055
	(0.0007)	(0.0014)	(0.0025)	(0.0039)	(0.0041)
Market	-0.0011^{***}	-0.0021^{***}	-0.0043^{***}	-0.0081^{***}	-0.0147^{***}
	(0.0003)	(0.0005)	(0.0008)	(0.0012)	(0.0040)
			β^J_{MV}		
Low-R&D	1.00^{*}	2.03^{***}	2.86^{***}	3.69^{***}	4.17^{**}
	(0.58)	(0.60)	(0.92)	(1.19)	(1.72)
High-R&D	0.83^{*}	2.08^{***}	3.60^{***}	4.96^{***}	6.29^{**}
	(0.45)	(0.43)	(0.90)	(1.53)	(2.60)
HML-R&D	-0.16	0.05	0.74	1.27	2.12^{*}
	(0.35)	(0.45)	(0.68)	(0.97)	(1.09)
Market	0.31	0.88^{*}	1.12^{**}	1.54^{**}	1.71
	(0.46)	(0.47)	(0.48)	(0.62)	(1.08)

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for both our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are equal-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. We only include firms with positive R&D expense in our cross-section. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table A9: ***DGDP*** **and Predictability of Returns to Innovation (Positive R&D Firms-VW)**

Horizon (J)	1	2	4	8	20
			β^J_{DGDP}		
Low-R&D	0.13***	0.26***	0.54***	1.09***	2.34***
	(0.03)	(0.06)	(0.14)	(0.28)	(0.60)
R^2	0.04	0.09	0.17	0.28	0.29
High-R&D	0.21***	0.40***	0.81***	1.58***	4.02***
	(0.03)	(0.06)	(0.13)	(0.23)	(0.58)
R^2	0.08	0.13	0.23	0.38	0.58
HML-R&D	0.08***	0.14***	0.27***	0.50***	1.68***
	(0.02)	(0.04)	(0.07)	(0.11)	(0.31)
R^2	0.08	0.13	0.23	0.38	0.58
Market	0.11***	0.22***	0.44***	0.87***	1.87***
	(0.02)	(0.05)	(0.10)	(0.21)	(0.52)
R^2	0.05	0.11	0.19	0.33	0.47

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative excess return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are value-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. We only include firms with positive R&D expense in our cross-section. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table A10: *PD, MV* and Predictability of Returns to Innovation (Pos. R&D Firms-VW)

Horizon J	1	2	4	8	20
			β^J_{PD}		
Low-R&D	-0.0010^{***}	-0.0020^{***}	-0.0043^{***}	-0.0087^{***}	-0.0151^{***}
	(0.0003)	(0.0006)	(0.0011)	(0.0019)	(0.0040)
High-R&D	-0.0010^{**}	-0.0019^{***}	-0.0040^{***}	-0.0066^{***}	-0.0117^{***}
	(0.0004)	(0.0007)	(0.0012)	(0.0018)	(0.0034)
HML-R&D	0.0000	0.0001	0.0003	0.0021^{*}	0.0034^{*}
	(0.0000)	(0.0006)	(0.0009)	(0.0012)	(0.0019)
Market	-0.0011^{***}	-0.0021^{***}	-0.0043^{***}	-0.0081^{***}	-0.0147^{***}
	(0.0003)	(0.0005)	(0.0008)	(0.0012)	(0.0040)
			β^J_{MV}		
Low-R&D	0.15	0.64	1.00	1.87	2.13
	(0.31)	(0.49)	(0.81)	(1.31)	(1.33)
High-R&D	0.53^{*}	1.08^{**}	1.70^{**}	2.50^{**}	3.20^{**}
	(0.29)	(0.49)	(0.78)	(1.27)	(1.31)
HML-R&D	0.38^{**}	0.45	0.70	0.63	1.07^{*}
	(0.18)	(0.35)	(0.55)	(0.77)	(0.57)
Market	0.31	0.88^{*}	1.12^{**}	1.54^{**}	1.71
	(0.46)	(0.47)	(0.48)	(0.62)	(1.08)

Notes: This table shows results from the following predictive regression:

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J},$$

where $R_{t\to t+J} := \sum_{j=1}^{J} r_{t+j}$ is the J-quarter-ahead cumulative return, PD denotes the aggregate price-dividend ratio, and MV refers to market integrated volatility. We report results for both our bottom-10 (*Low-R&D*) and top-10 (*High-R&D*) portfolios, the full market portfolio, and a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*). Returns are value-weighted. Innovation intensity is measured as the ratio of R&D expenses to total assets. We only include firms with positive R&D expense in our cross-section. Our quarterly sample is 1966:Q2–2013:Q4. Newey-West (1987) standard errors are in parentheses. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

In table A11 we sort portfolios according to the Lin (2012) measure of innovation intensity, i.e., the ratio of R&D and capital expenditure. As in the analysis presented in the main text, we find that *DGDP* predicts higher *HML-R&D*.

Table A11: Conditional Macro Factors Model (II)

	$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$	
	EW	VW
Low–R&D	0.05***	0.14***
	(0.02)	(0.03)
High–R&D	0.15***	0.22***
	(0.03)	(0.03)
HML–R&D	0.10***	0.09***
	(0.01)	(0.02)
Market	0.11***	0.20***
	(0.02)	(0.03)
Small–Low B/M	0.15***	0.24***
	(0.03)	(0.04)
Small–High B/M	0.14***	0.23***
	(0.03)	(0.03)
Big–Low B/M	0.12***	0.20***
	(0.02)	(0.04)
Big–High B/M	0.07***	0.15***
	(0.02)	(0.03)

	EV			VW		
	$\Delta DGDP$	ΔTFP	ΔGY	$\Delta DGDP$	ΔTFP	ΔGY
Price of risk, λ	-0.002	0.008***	-0.020***	-0.016***	0.010***	-0.028***
	(0.003)	(0.001)	(0.003)	(0.004)	(0.001)	(0.005)
J-Test		8.54			8.54	
p-value		1.00			1.00	

Notes: This table shows results from our GMM estimation of the conditional macro factor model detailed in the system of equations (25). Our macro factors consist of changes to debt-to-output ratio ($\Delta DGDP$), government spending-to-output (ΔGY), and TFP (ΔTFP). In the top portion of the table, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t = \sum_{j=1}^{J} \beta_j^{1i}\lambda_j$, where λ_j denotes the market price of risk for factor j. EW (VW) denotes equally-weighted (value-weighted) returns. Our portfolio are sorted on R&D-to-capital expenditure (capx) as in Lin (2012). The set of test assets includes: our bottom-10 (Low-R&D) and top-10 (High-R&D) portfolios; our 'Middle' portfolio; a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*); the Fama-French 25 size/book-market-sorted portfolios; and the full market portfolio. Newey-West (1987) standard errors are in parentheses. Data are from 1966:Q2 to 2013:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Our J-Test is based on 27 degrees of freedom.

In table A12, we confirm that our predictability results also hold when we focus only on positive-R&D firms.

Table A12: Conditional Macro Factors Model – Positive R&D Firms

	$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$	
	EW	VW
Low–R&D	0.10***	0.07***
	(0.03)	(0.02)
High–R&D	0.16***	0.16***
	(0.04)	(0.03)
HML–R&D	0.05**	0.08***
	(0.02)	(0.02)
Market	0.14***	0.16***
	(0.03)	(0.03)
Small–Low B/M	0.17***	0.19***
	(0.03)	(0.04)
Small–High B/M	0.16***	0.19***
	(0.03)	(0.04)
Big–Low B/M	0.13***	0.15***
	(0.03)	(0.04)
Big–High B/M	0.10***	0.13***
	(0.03)	(0.03)
SMB	0.02	0.02
	(0.02)	(0.02)
HML	−0.02	−0.01
	(0.02)	(0.02)

	EW			VW		
	$\Delta DGDP$	ΔTFP	ΔGY	$\Delta DGDP$	ΔTFP	ΔGY
Price of risk, λ	−0.006*	0.008***	−0.020***	−0.012***	0.009***	−0.019***
	(0.003)	(0.001)	(0.003)	(0.004)	(0.001)	(0.004)
J-Test		31.80			38.80	
p-value		1.00			0.99	

Notes: This table shows results from our GMM estimation of the conditional macro factor model detailed in the system of equations (25). Our macro factors consist of changes to debt-to-output ratio ($\Delta DGDP$), government spending-to-output (ΔGY), and TFP (ΔTFP). In the top portion of the table, $\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t = \sum_{j=1}^{J} \beta_j^{1i}\lambda_j$, where λ_j denotes the market price of risk for factor j. EW (VW) denotes equally-weighted (value-weighted) returns. The set of test assets includes: our bottom-10 (Low-R&D) and top-10 (High-R&D) portfolios; our 'Middle' portfolio; a portfolio long in our high-R&D stocks and short in our low-R&D stocks (*HML-R&D*); the Fama-French 25 size/book-market-sorted portfolios; and the full market portfolio. We only include firms with positive R&D expense in our cross-section. Newey-West (1987) standard errors are in parentheses. Data are from 1966:Q2 to 2013:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Our J-Test is based on 29 degrees of freedom.

Table A13 uses financial constraints adjusted returns to evaluate the conditional 3-factor macro model.

Table A13. Conditional Macro Factors Model – Financially Constrained Adjusted Returns

	KZ Index Price of risk, λ				SA Index Price of risk, λ			
	TWX		OLS		TWX		OLS	
	Est	SE	Est	SE	Est	SE	Est	SE
$DGDP$	-0.012^{***}	0.002	-0.013^{***}	0.003	-0.009^{***}	0.002	-0.011^{***}	0.002
TFP	0.006^{***}	0.001	0.007^{***}	0.001	0.006^{***}	0.001	0.006^{***}	0.001
GY	-0.027^{***}	0.004	-0.026^{***}	0.004	-0.026^{***}	0.004	-0.027^{***}	0.003
	$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$				$\partial E_t(R^{ex}_{i,t+1})/\partial DGDP_t$			
	Est	SE	Est	SE	Est	SE	Est	SE
HML-R&D	0.070^{**}	0.034	0.073^{**}	0.031	0.069^{***}	0.024	0.072^{***}	0.019

Notes: This table shows the main macro model when we use financially constrained adjusted returns in our R&D portfolios. The model is estimated using characteristic adjusted returns from Titman, Wei, and Xie (2004) (TWX) as well as residuals (OLS) from returns regressed contemporaneously on the financial constraint indices. The KZ index is constructed following Kaplan and Zingales (1997) and the SA index is constructed following Hadlock and Pierce (2010). We present Newey-West (1987) standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Data are from 1975:Q1 to 2013:Q4.

B Tax Rate Dependence on the Debt-to-Output Ratio

Let $BY_t = \frac{B_t}{Y_t}$ denote the debt-to-output ratio in the economy at time t, and assume that authorities are planning to bring this ratio from an initial level of BY_0 to $BY_0 - \delta$ in T periods. Assume that output grows at a constant average rate of g, $Y_t = Y_0(1+g)^t$.

Given an initial level of debt B_0, the law of motion for the debt level is

$$B_t = B_{t-1}(1+r) - \tau Y_{t-1},\ t \geq 1,$$

where τ is the average tax rate over T periods and r is the constant interest rate on the government's debt. We abstract away from additional expenditures without loss of generality. Iterating this equation forward, we obtain

$$B_t = B_0(1+r)^t - \tau Y_0 \left[\sum_{i=0}^{t-1}(1+r)^i(1+g)^{(t-1)-i}\right]. \tag{27}$$

Given the target of the authorities, $B_T = (BY_0 - \delta)Y_0(1+g)^T$, the implied equilibrium τ is

$$\tau = \frac{B_0(1+r)^T - B_T}{Y_0\left[\sum_{i=0}^{T-1}(1+r)^i(1+g)^{(T-1)-i}\right]}, \tag{28}$$

and it simplifies further if we assume that $r = 0$:

$$\tau \quad = \quad \left[\frac{\delta(1+g)^T}{(1+g)^T - 1} - G_0\right] g.$$

As a result, we obtain the following conditions:

$$\frac{\partial^2 \tau}{\partial g \partial G_0} < 0$$
$$\frac{\partial \left|\frac{\partial \tau}{\partial g}\right|}{\partial |G_0|} > 0,$$

which imply that higher levels of the debt-to-output ratio increase the volatility of the tax rate under uncertainty about the growth rate of the economy. Below we report the change in average tax rate when growth ranges from -3% to $+3\%$ for both a high (50%) and a low (20%) initial ratio of debt to output with a targeted reduction δ of 20%. The range of the implied τ captures the extent of tax rate volatility.

Table B1: Avg. Tax Rate in High and Low Debt/GDP Environments

	Target Debt/GDP	
	50%–30%	20%–0%
-3% Growth	3.18%	2.28%
3% Growth	0.84%	1.75%
Tax Rate Range	2.34%	0.54%
	Change in Range	**1.80%**

C Empirical Specifications

C.1 Parameterized β Regressions

We decompose the coefficient β^J_{DGDP} defined in the following regressions,

$$R_{i,t\to t+J} = \beta_{i,0} + \beta^J_{i,DGDP} DGDP_t + \epsilon_{i,t+J}, \tag{29}$$

as follows

$$\beta^J_{i,DGDP} = \beta(J)[1 + \gamma(rd_i - \bar{rd})], \tag{30}$$

where rd_i is the time-series average of the R&D intensity of portfolio i; $\bar{rd}$ is the overall average of R&D intensity; and $\beta(J)$ is a horizon-specific coefficient. We then jointly estimate $\theta = (\beta(1), \beta(2), \beta(4), \beta(8), \beta(20), \gamma)$ in a GMM setting with the appropriate orthogonality restrictions implied by equation (29).[13]

The multivariate case is analogous, where $X_{i,J}$ is now the OLS design matrix related to Equation (31).

$$R_{t\to t+J} = \beta_0 + \beta^J_{DGDP} DGDP_t + \beta^J_{PD} PD_t + \beta^J_{MV} MV_t + \epsilon_{t+J}. \tag{31}$$

[13] We focus on the following quadratic objective function:

$$Q_n(\theta) = \sum_{i,J} [\iota_2' (X_{i,J}' X_{i,J})^{-1} (X_{i,J}' R_{i,J}) - \beta(J)[1 + \gamma(rd_i - \bar{rd})]]^2,$$

where $X_{i,J}$ is the OLS design matrix related to Equation (29) and $R_{i,J}$ is the stacked cumulative returns, both for portfolio i and horizon J. We define ι_2 to be a conformable zeros column vector with a one in the 2nd position.

C.2 TFP Construction

We use the following Solow residual method to create the TFP series used in the predictive regressions for TFP growth:

$$\Delta TFP_t = \Delta GDP_t - \alpha \Delta L_t - (1-\alpha)\Delta K_t. \tag{32}$$

Labor growth is the log difference of the FRED series "Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing". We use real physical investment excluding R&D expenditures ($I = Inv - R\&D$) to create our physical capital series. Nominal series are transformed to real using the GDP deflator. Physical capital evolves using the law of motion $K_t = (1-\delta)K_{t-1} + I$, where δ is the quarterly capital depreciation rate. We initialize the capital series in 1975:Q1 using the perpetuity formula $K_{1975:Q1} = \frac{I_{1975:Q1}}{\delta}$. We set the parameters $\delta = 0.02$ and $\alpha = 0.58$ as in our calibration.

C.3 Look-ahead Bias Correction

We first estimate the following equation using a rolling window size of 32 quarters,

$$R^{HML-R\&D}_{t\to t+J} = \beta^J_0 + \beta^J_{DGDP} \cdot DGDP_t + \beta^J_{PD} \cdot PD_t + \beta^J_{MV} \cdot MV_t + \epsilon_{t+J}. \tag{33}$$

From this estimation, we store the end-period fitted values for $\{\widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right), \widehat{\epsilon_{t+J}}\}$, where

$$\widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right) = \widehat{\beta^J_0} + \widehat{\beta^J_{DGDP}} \cdot DGDP_t + \widehat{\beta^J_{PD}} \cdot PD_t + \widehat{\beta^J_{MV}} \cdot MV_t \tag{34}$$

$$\widehat{\epsilon_{t+J}} = R^{HML-R\&D}_{t\to t+J} - \widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right). \tag{35}$$

This method guarantees that only information up to time t was used to construct fitted values for periods $t+J$. We then use this sequence of $\{\widehat{E}_t\left(R^{HML-R\&D}_{t\to t+J}\right), \widehat{\epsilon_{t+J}}\}$ to estimate

the following regression:

$$\Delta GDP_{t\to t+J} = c_0^J + c_1^J \cdot \widehat{E}_t \left(R_{t\to t+J}^{HML-R\&D} \right) + c_2^J \cdot \widehat{\epsilon_{t+J}} + v_{t+J}. \tag{36}$$

C.4 Stambaugh Bias Correction

We follow the methods in Stambaugh (1999) and use the sample counterpart of equation **(18)** to correct for bias in our univariate predictive return regressions. The method is also explained in Stambaugh (1986), equation 11. We report bootstrapped standard errors for this procedure, and use a block bootstrap with a block size of $T/4$.

C.5 Characteristic-Adjusted Returns

We follow Titman, Wei, and Xie (2004) in constructing returns adjusted for the impact of both financial constraints and financial leverage (secondary sorting characteristic).

Each year, we first sort firms by their secondary sorting characteristic into three portfolios whereby both the low and high portfolios are guaranteed to contain firms totaling 10% of the overall market capitalization. These portfolios are re-formed each year. Quarterly stock returns are then adjusted by taking each firm's quarterly return and subtracting the cross-sectional average quarterly returns of the secondary sorting characteristic portfolio that the firm is a member of. Firms are then sorted according to our baseline procedure based on R&D intensity.